Research article

Energy saving and management of water pumping networks

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ABSTRACT

The main consumption of energy in water systems is the pumps. Due to the different tariff of energy consumption during the one day, the operation of these pumps should be controlled to minimize their consumption and consequently decrease the cost of operation. This paper utilizes an optimization algorithm to control the on/off operation of water pumps to minimize the cost of energy consumption and number of pump switching of water networks. This objective function is subjected to some optimization and hydraulic constraints such as the tanks upper and lower limits, and water network pressure limit. The proposed methodology is an iterative combination process between an optimization algorithm and EPANet hydraulic simulator where optimization algorithm generates the schedules and the hydraulic simulator is used to check the feasibility of these schedules. The suggested optimization method is the artificial electric field algorithm (AEFA). This methodology is applied to three water networks; EPANet practical example network, Richmond network and a part from Toronto network with a variable energy consumption tariff. The AEFA is tested and trained to select the best values of its controlling parameters for each network. The results show that the energy consumption cost is significantly decreased by the optimal schedules of water pumps. Also AEFA is compared with other optimization algorithms such as the genetic and particle swarm algorithms on the same networks and energy tariff and the results show the superiority of AEFA in the convergence and saving of the cost of energy consumption.

1. Introduction

In water utilities, the main consumer of the electric energy is the water pumps where they consume from 90 to 95% of the total consumed energy of water utilities. This means that the biggest operating disbursements for water utilities are costs of pumping consumption [1]. As an example, in United States, about 4 % of the energy usages is for water distribution and treatments [2]. In Toronto city as another example, the water consumption is almost five times the energy consumption of traffic signals and street lights [3].

With using fixed energy consumption tariff, the optimal pump schedules are to fulfil hydraulic and operation constraints such as water network pressure, nodes head, and the upper and lower limits of the water and the energy consumption saving is achieved by decreasing energy losses due to pipe friction and water leakages. Recently, the attention to optimal pumps schedules is raised due to the variable energy consumption tariff that is offered by the electric utilities where electric utilities offer high energy tariff at the high demand and low energy tariff at low energy demand during the same day [4].

Due to the complex nonlinear constraints of the water pump scheduling problem, the major of the proposed solutions depend on the on- or off-line simulation process to avoid the treatment of these constraints. The on-line relies on calling the hydraulic simulation tool, as subroutine program, to check the hydraulic feasibility of the schedules [5]. In [6], authors have introduced hybrid methodology to find the optimal water pump scheduling and they have utilized EPANet hydraulic simulation software [7] to test the feasibility. On the other hand, the off-line simulation relies on generating a prior response to the solution (i.e daily energy cost tariff) using the hydraulic simulator [8].

Many researchers have worked to find the optimal schedules of different water networks. In [9], the authors have proposed a hybrid method of the strength pareto evolutionary algorithm and EPANet hydraulic simulator to trade-off pumps operational costs. The genetic algorithm has been introduced to optimal schedules of water pumps in EPANet Net3 example based on three different objective functions; minimizing the pumps energy consumption, controlling the water flow balance and increasing the system efficiency [10]. Also the genetic algorithm (GA) was used with another authors to find a solution of this
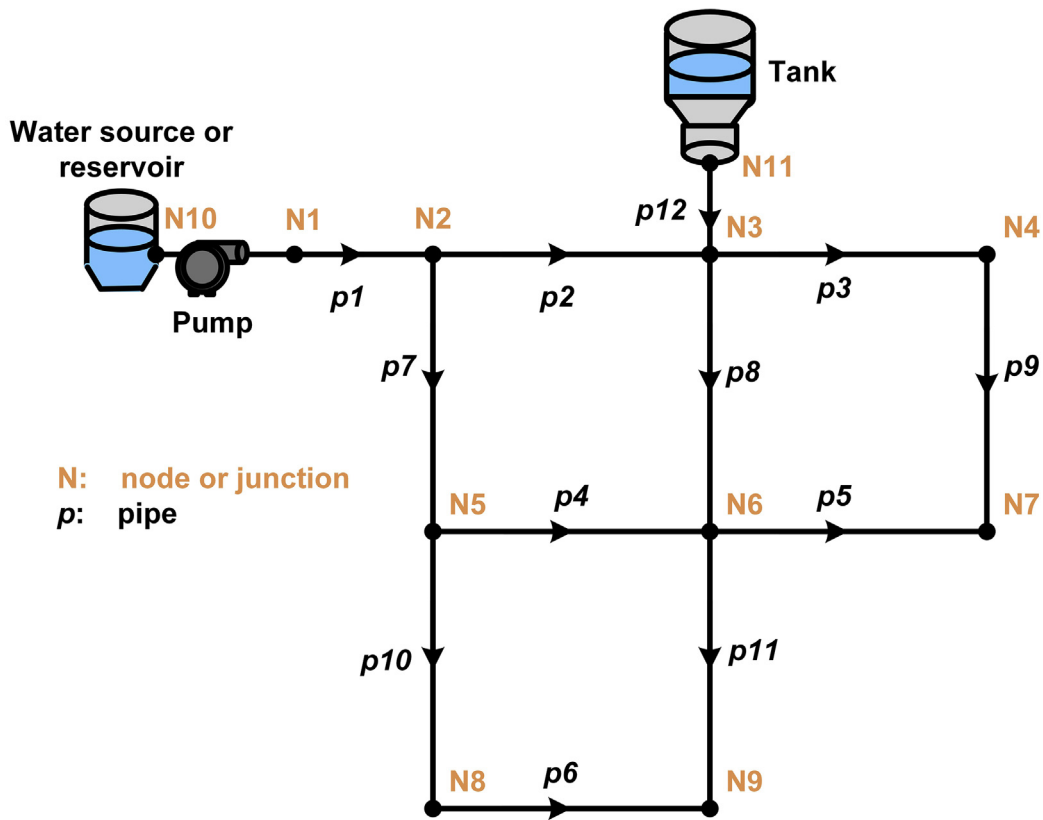
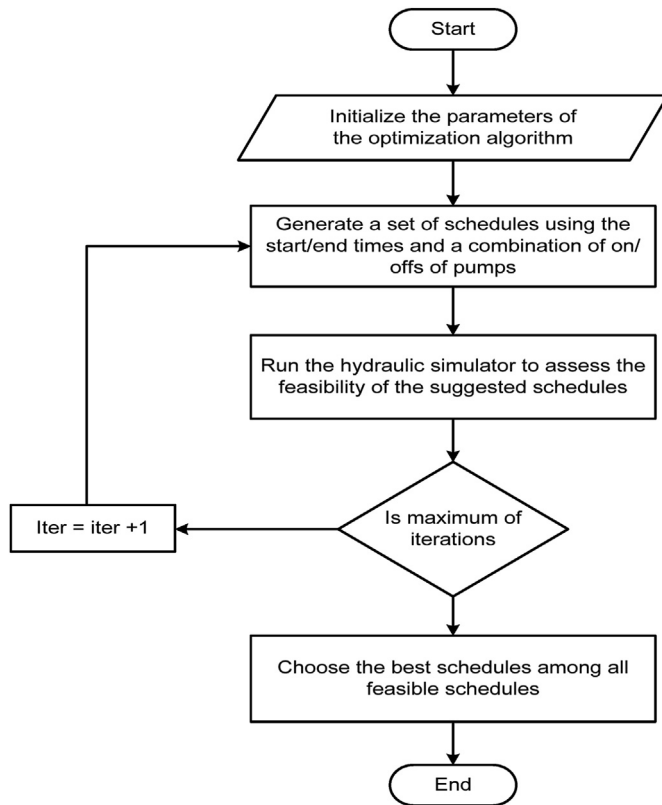**Figure 1.** Water pump network parameters.

Figure 2. The flowchart of the proposed methodology.

problem but they had used a different objective function that is minimizing the cost and protecting the environment [11]. In [12], the authors have introduced the convex mathematical algorithm to find the optimal schedules for the water distribution network (WDN) and they have compared the results with an operational scenario used historical data to assess the robustness, financial saving and convergence of their algorithm. In [13], the Lagrangian decomposition method is proposed and validated by comparing its results with the mixed integer nonlinear programming (MILP) method. MILP method has been used in [14] to find the optimal scheduling of water cooling system. Also MILP has been used in [15] to increase the use of pumps in the overnight time that is a low cost energy time. Some researchers have tried to calculate a penalty factor of the objective function, this term relies on the pumps failure and the network pressure, and they have solved this problem by genetic algorithm [16]. The Levenberg Marquardt method has been proposed to optimize the operation of parallel pumps by variating the speed [17]. A hybrid algorithm based on the rigorous description of the losses of water pipe lines and MILP has been introduced to solve this problem [18]. Other heuristic algorithms have been presented to solve this problem such as simulated annealing [19], particle swarm optimization (PSO) [20].

The artificial electric field algorithm (AEFA) is a modern optimization technique that is formulated based on the coulomb's laws and the second law of Newton. The researchers have given AEFA a great attention and they used to solve the optimization problems in several research areas such as optimal parameters estimation [21, 22], capacitor bank allocation [23], scheduling [24] and phasor measurement units allocation [25]. There are some similarities between AEFA and PSO; (1) they are optimization algorithms depend on population and (2) the optimal solution is found by the motion of particles.

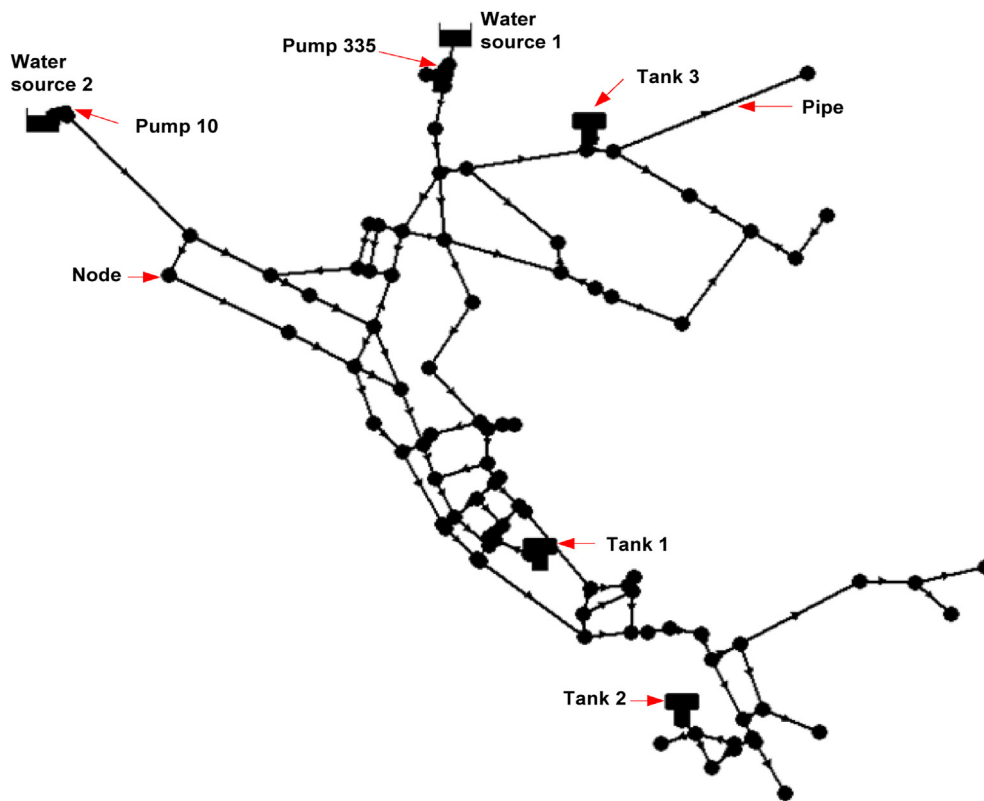The main contributions of this paper are:
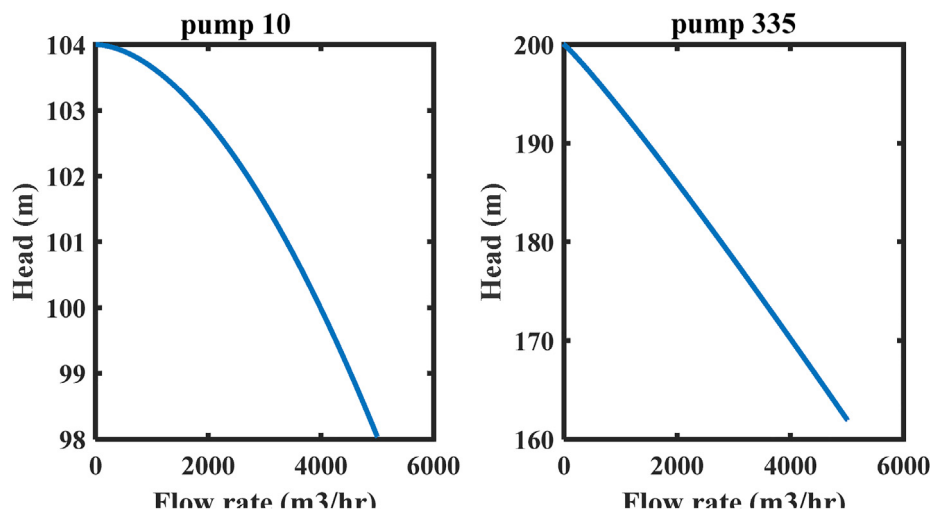
Figure 3. EPANet Net3 water network.

Figure 4. Characteristic curve of network pumps.

Table 1. The upper and lower limits of the water tanks of EPANet Net3 WDN.

Tank	1	2	3
Lower limit (m)	6.5	6.5	6
Upper limit (m)	9	8.5	9

i) Proposing a hybrid methodology of AEFA as a modern optimization method and EPANet as a hydraulic simulator to solve the problem of optimal water pumps scheduling.

ii) Formulating the objective function to minimize the cost of the consumed energy of water pumps, to minimize the maintenance

cost by decreasing the number of switching on/off of the pumps and to decrease the water demand charge.

iii) The AEFA is used to generate many schedules and the EPANet is used to assess the hydraulic feasibility of these generated
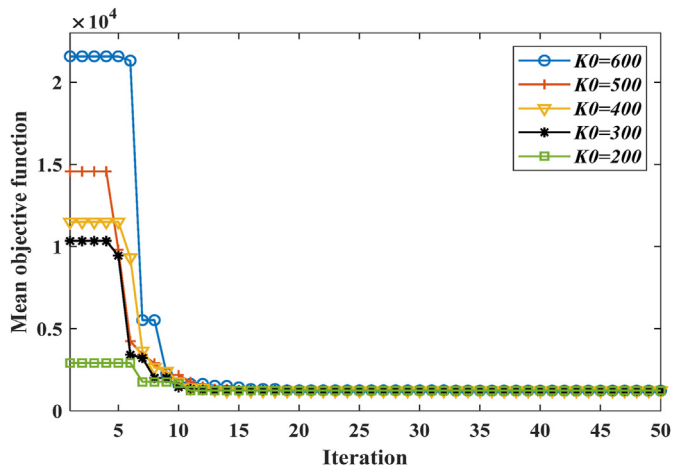
Figure 5. The influence of K_0 on the performance of AEFA.

schedules and to ensure the fulfil of the hydraulic constrains such as the tanks level boundaries and the water network pressure.

iv) Applying the proposed methodology on EPANet example water network, Richmond water network in UK and part of Toronto city water network on a variable tariff of energy.

v) The results of AEFA are compared with those of the genetic algorithm and particle swarm algorithms on the same networks and the same energy tariff.

Accordingly, this paper is organized as follows. In section 2, the problem formulation is presented. Section 3 introduces the proposed AEFA and how it is implemented to solve the problem. In section 4, the results of applying the proposed approach on experimental data are discussed. Finally, the conclusions are presented in section 5.

2. Problem formulation

The objective function and constraints are formulated in this section. Water networks contain unlimited sources or reservoirs, pumps, tanks, pipes and demand nodes, as shown in Figure 1. This work is based on the knowledge of tanks upper and lower limits, and daily energy consumption tariff. The water flow through the pump and supplied head are calculated using the known hydraulic simulator EPANet.

2.1. The objective function

In this work, a multi-term objective function is introduced. Where the objective function is to minimize the cost of the electric energy consumption, pump maintenance and the demand charge.
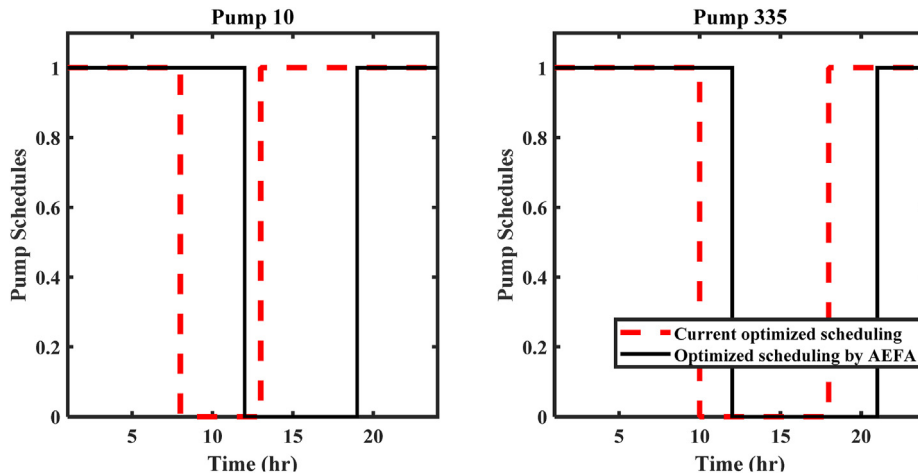

Figure 6. The optimal water scheduling of pump 10 and pump 335.
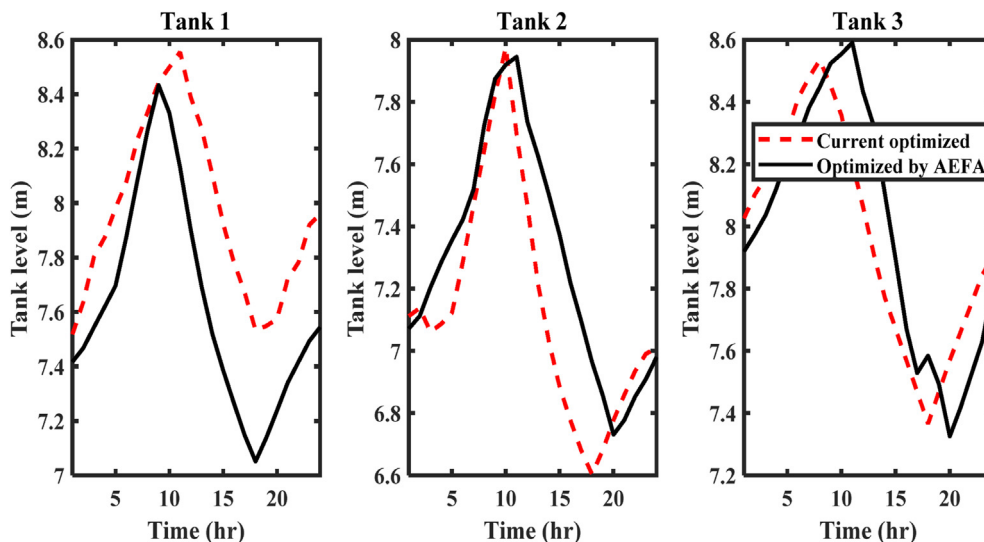

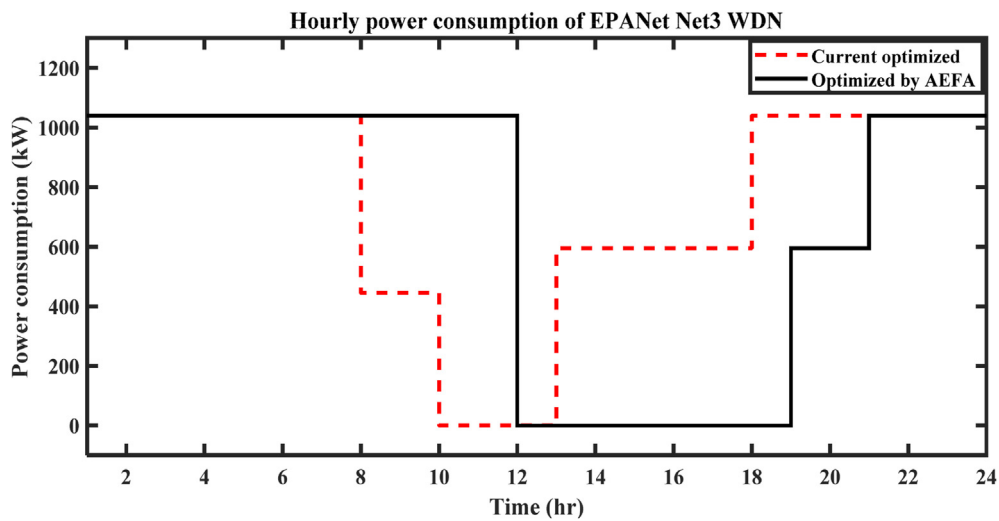**Figure 7.** Tanks daily water level of Net3 water network.

Figure 8. The daily power consumption of the Net3 water network.

Table 2. Results of EPANet Net3 water network.

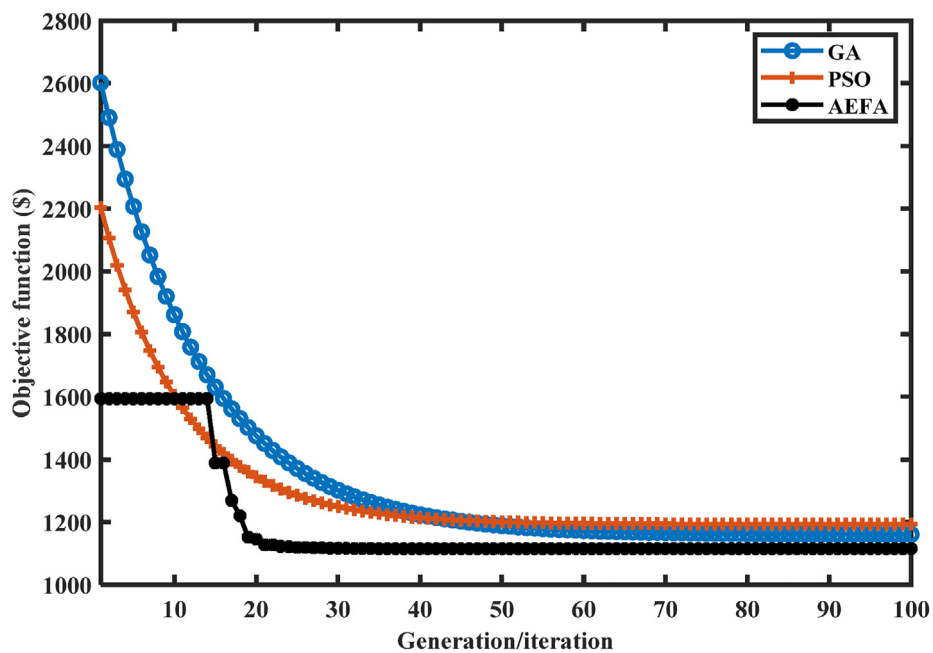|	Current optimized scheduling	Optimized scheduling by AEFA
Energy cost (f_1) ($)	1297.3	1045.5
Demand charges (f_2) ($)	121	103
Maximum number of switching for all pumps	4	4
Maintenance cost (f_3) ($)	4	4
Total cost ($)	1367.3	1115.5

Figure 9. The convergence comparison of AEFA with GA and PSO for EPANet Net3.

Table 3. Comparison between GA, PSO and the proposed AEFA for EPANet Net3.

Algorithm	No of generation\iteration	Objective function	Percentage cost saving
GA	65	1161	15.1 %
PSO	60	1194	12.7 %
AEFA	21	1115.5	18.4 %
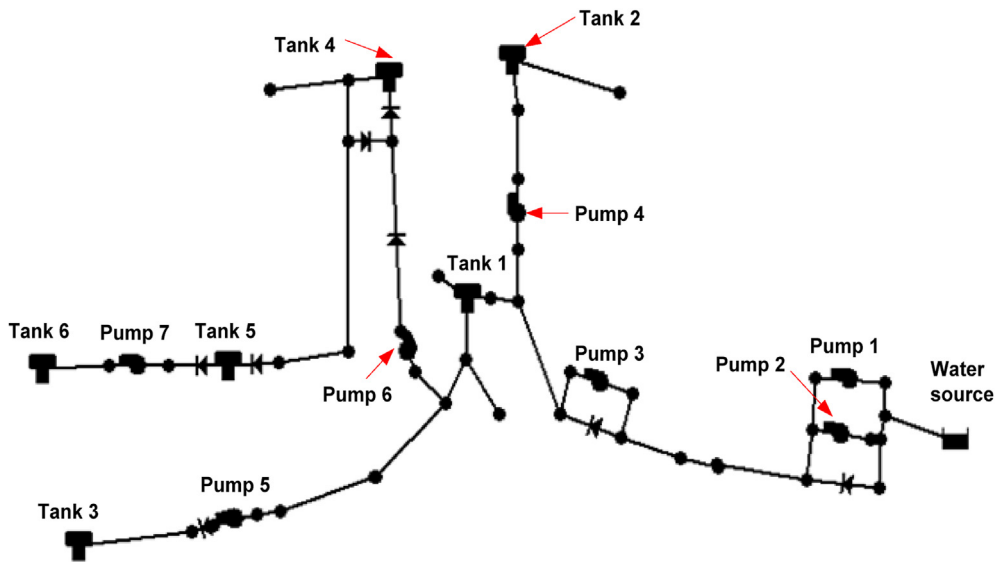
Figure 10. Richmond water network.

Table 4. Power and flow ratings of pumps [31].

Pump	#1	#2	#3	#4	#5	#6	#7
Power (kW)	595	445	260	260	595	740	330
Water Flow (m³/hr)	1800	1440	828	828	1800	2240	1000
Start node	2009	1963	175	1250	635	264	745
End node	766	768	186	253	636	1125	753
Pump curve	2007	2015	1006	1881	1884	1123	1883

$$Objective\ function = min(f_1 + f_2 + f_3) \tag{1}$$

where f_1 is the cost of electric energy consumption, f_2 is the pump switch penalization and f_3 is the cost of demand charges. These costs are explained in details as follow:

2.1.1. The cost of energy consumption

The consumed power by a pump i during the time period j, where j represents one hour, depends on the pump efficiency (η), the pump discharge (q) and head of the pump (h) as follow:

$$P_{ij} = \rho_i^j \frac{q_i^j \times h_i^j}{\eta_i} \tag{2}$$

where ρ_i^j is a conversion coefficient specifies the water weight and hour of use.

The cost of the pumps energy consumption of a 24 h is:

$$f_1 = \sum_{i=1}^{np} \sum_{j=1}^{24} x_{ij} * P_{ij} * c_{e_j} \tag{3}$$

where

  np: pumps number,
  P_{ij}: required power of pump i at the time instant j,
  c_{e_j}: cost of energy consumption at time instant j.
  x_{ij} is the state of pump i at the time instant j

2.1.2. The pump switch penalization

To conserve mechanical wear and maximize operational reliability supply system, excessive pump switching is introduced into the optimization objective. The pump switching is defined as the change of pump status from on state to off state or from off state to on state. Minimizing the number of pump switching can be achieved by increasing the time duration between two operation interval.

$$f_2 = \sum_{i=1}^{np} c_m * Sw_{max_i} \tag{4}$$

where

  c_m: switch penalty constant of pump i per one switching,
  Sw_{max_i}: maximum number of pump i switching.

2.1.3. The cost of demand charges

$$f_3 = c_d * P_{max} \tag{5}$$

  c_d: cost of demand charge,
  P_{max}: maximum demand charge.

This objective function is subjected to the following types of constraints:

2.1.3.1. Optimization constraints.

• *Number of switching on/off of pumps limits*

$$N_{Sw,min} \leq Sw_{max_i} \leq N_{Sw,max} \tag{6}$$

where Sw_{max_i} is the maximum number of switching of pump i at the end of scheduling period, $N_{Sw,min}$ is the minimum allowable number of switching and $N_{Sw,max}$ is the maximum allowable number of switching.
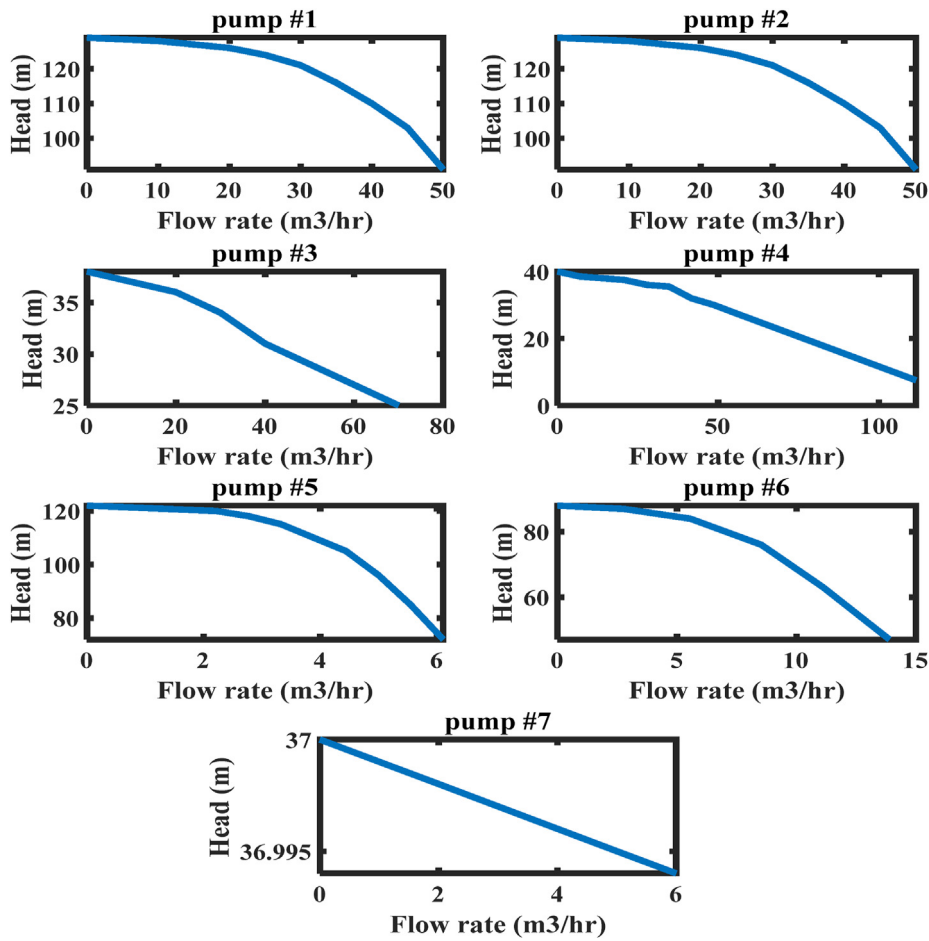
Figure 11. The characteristic curves of Richmond WDN pumps.

Table 5. The upper and lower limits of the water tanks of Richmond WDN [31].

Tank	1	2	3	4	5	6
Lower limit (m)	1.01	2.03	0.5	1.1	0.2	0.19
Upper limit (m)	3.37	3.65	2	2.11	2.69	2.19

Table 6. Energy tariff of Richmond water network [31].

Pump	Off Peak (£/kWh)	Peak (£/kWh)
#1	0.02410	0.0679
#2	0.02410	0.0679
#3	0.02410	0.0754
#4	0.02460	0.1234
#5	0.02460	0.0987
#6	0.02460	0.1120
#7	0.02440	0.1194

- *Pumps state*

x is the state of pump, where $x = 0$ if the pump is off and $x = 1$ if the pump state is on

$x_i \in \{0, 1\}$ $i = 1, 2, ..., np$

2.1.3.2. Water network constraints. The water network constraints represent the hydraulic state of network and these constraints are handled by the hydraulic simulator (EPANet). Bound constraints

evaluate the performance or feasibility of proposed pumps scheduling. These constraints include restrictions on the maximum and minimum water levels of the tank, combined water volume limits of all tanks and pressures at the nodes of demand. If any one of these constraints does not meet its limits, EPANET will generate warnings during the simulation that shows this scheduling is infeasible.

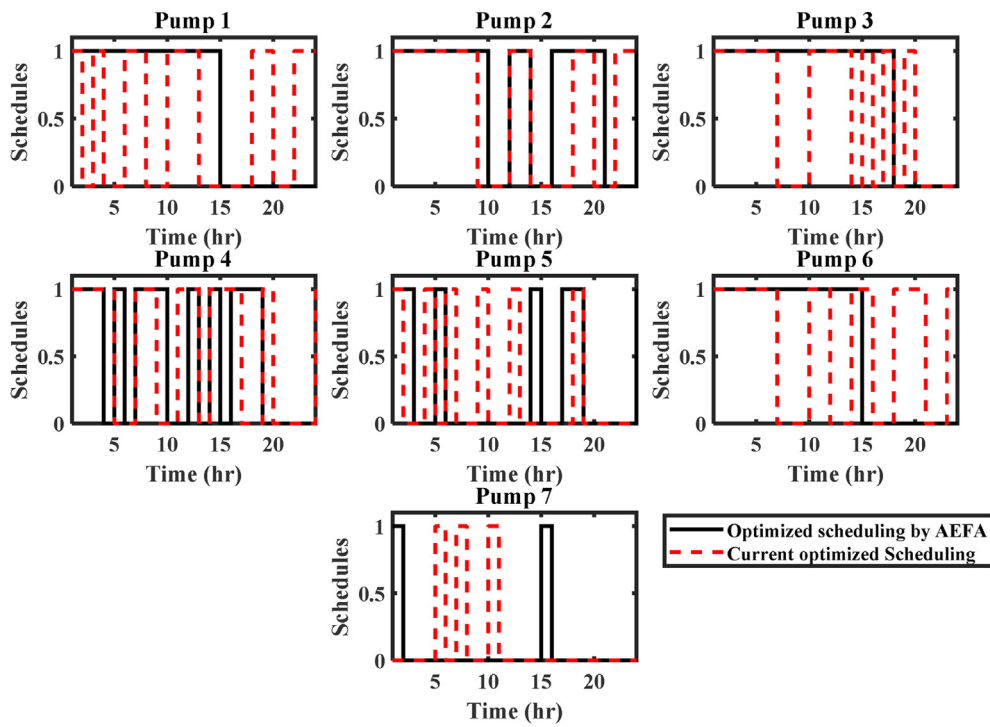- *Tanks upper and lower head limits*
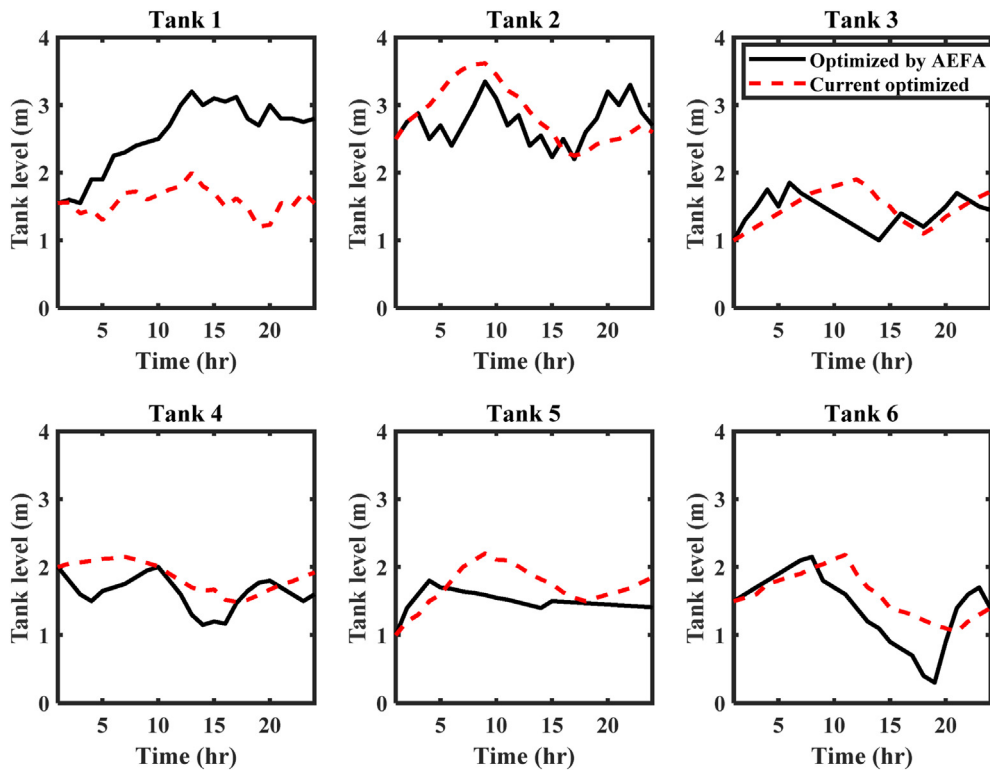
Figure 12. The scheduling of Richmond WDN pumps.

Figure 13. Water level of Richmond WDN tanks.

$$h_T^{j,lower} \leq h_T^j \leq h_T^{j,\,upper} \tag{7}$$

where $h_T^j,\ h_T^{j,lower}$ and $h_T^{j,\,upper}$ are the current tank head, lower head limit and upper head limit, respectively.

- *Combined water volume in all tanks at the end of the scheduling period*

The total water volume in all tanks at the end of the scheduling period should not be less than the total volume at the beginning of the scheduling period to fulfill the periodicity between supplies and demands. If there is a difference, this difference is called volume shortage. If the volume shortage of all tanks is not zero, this shortage will be added to the next scheduling and will increase the operation cost.
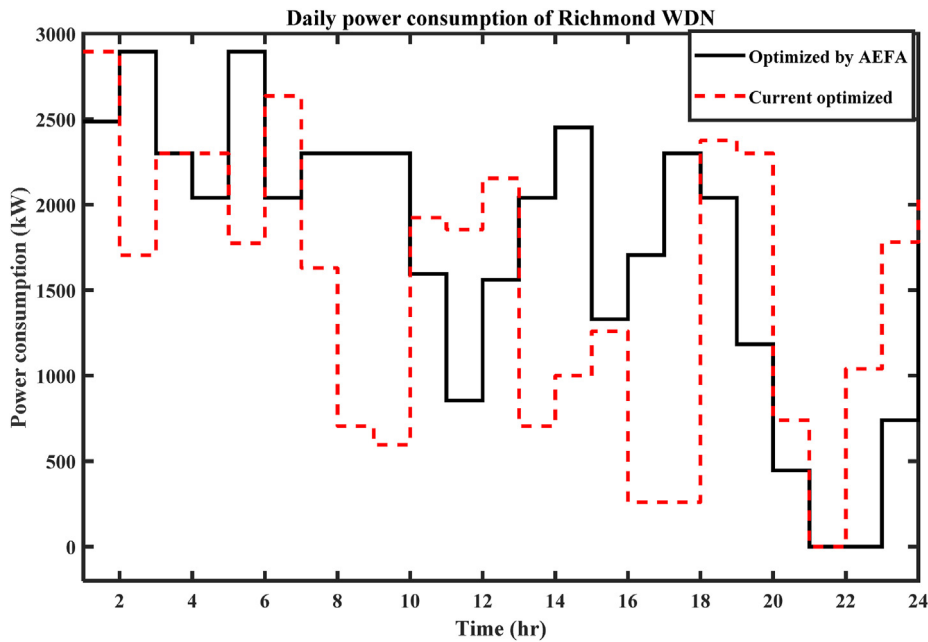
Figure 14. The power consumption profile per day for Richmond WDN.

Table 7. Results of Richmond water network.

	Current optimized scheduling	Optimized scheduling by AEFA
Energy cost (f_1) (£)	2,584.35	2,169.6
Demand charges (f_2) (£)	243	221
Maximum number of switching for all pumps	59	24
Maintenance cost (f_3) (£)	8.85	3.6
Total cost (£)	2,836.2	2,394.2

Table 8. Comparison between GA, PSO and the proposed AEFA for Richmond WDN.

Algorithm	No of generation\iteration	Objective function (£)	Percentage cost saving
GA	61	2426	14.4 %
PSO	54	2514	11.3 %
AEFA	23	2394.2	15.6 %

$$D_{min} \leq \frac{V_s - V_e}{V_e} \times 100 \leq D_{max} \tag{8}$$

$$V_s = \sum_{j=1}^{N_T} V_{sj} \tag{9}$$

$$V_e = \sum_{j=1}^{N_T} V_{ej} \tag{10}$$

where D_{min} and D_{max} are the parentage minimum and maximum allowable volume in all tank, respectively, V_s, V_e are the volume in all tanks at the start and end of the scheduling period, respectively and NT is the number of tanks.

- *The required water pressure limits in the water networks*

It is required that consumers are supplied water at adequate pressures. Therefore, the optimization model must include maximum and minimum pressure constraints at customer demand nodes and these pressure constraints are controlled by the EPANet simulator. EPANet returns the dynamic pressure heads and flow rate for each pump.

$$H_j^{min} \leq H_j \leq H_j^{max} \tag{11}$$

where H_j is the pressure at demand node j, H_j^{min} and H_j^{max} are the minimum and maximum required pressure limits, respectively.

3. The proposed solution algorithm and its implementation

3.1. Artificial electric field algorithm

In this work, the artificial electric field algorithm (AEFA) is utilized to fulfil the objective function that is stated in Eq. (1). AEFA is considered as a modern meta-heuristic technique that is formulated based on the laws of coulomb and the second law of Newton's. Coulomb deduced two laws to characterize the generated forces between any two electric charges. If the one charge has a positive polarity and the other has negative polarity, an attraction force will be generated and will force the charges to move to each other. If the two charges have a positive or negative polarity, a repulsion force will be generated and it will force the charges to move
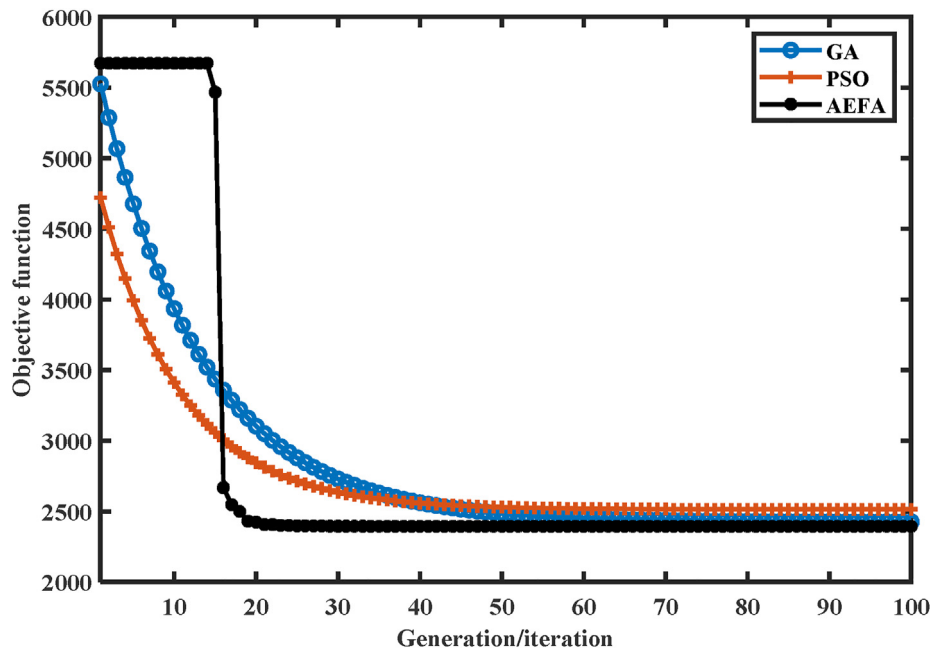
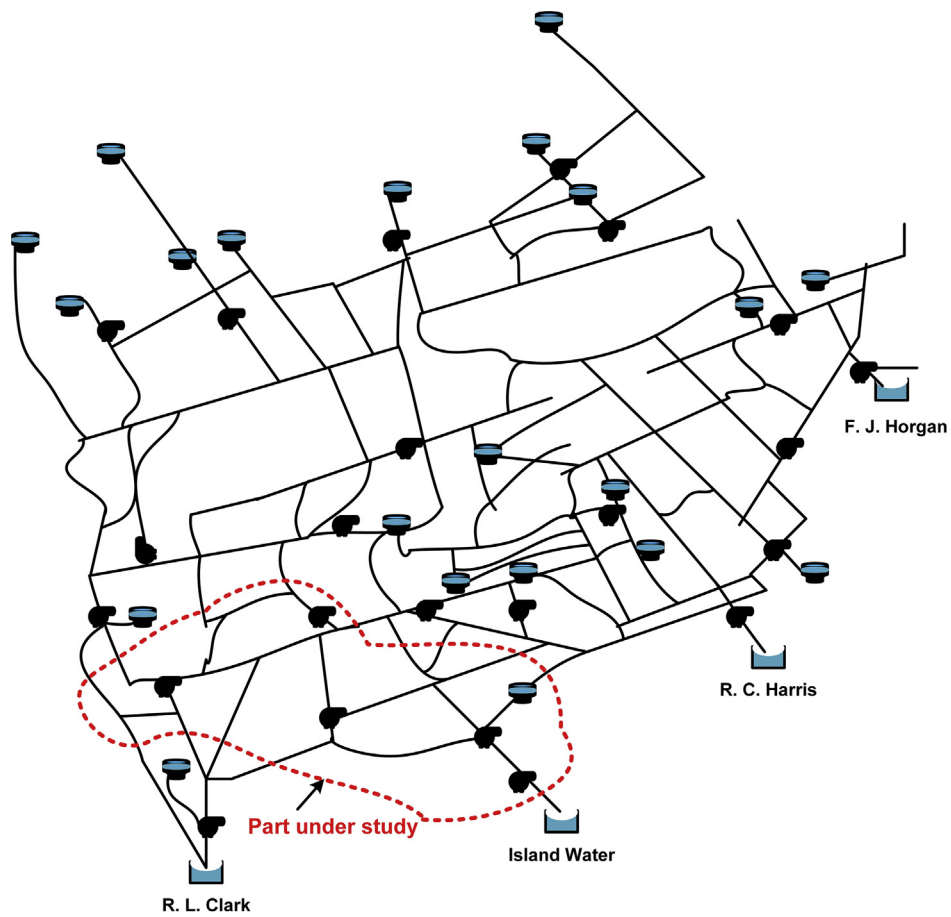**Figure 15.** The convergence comparison of AEFA with GA and PSO for Richmond WDN.

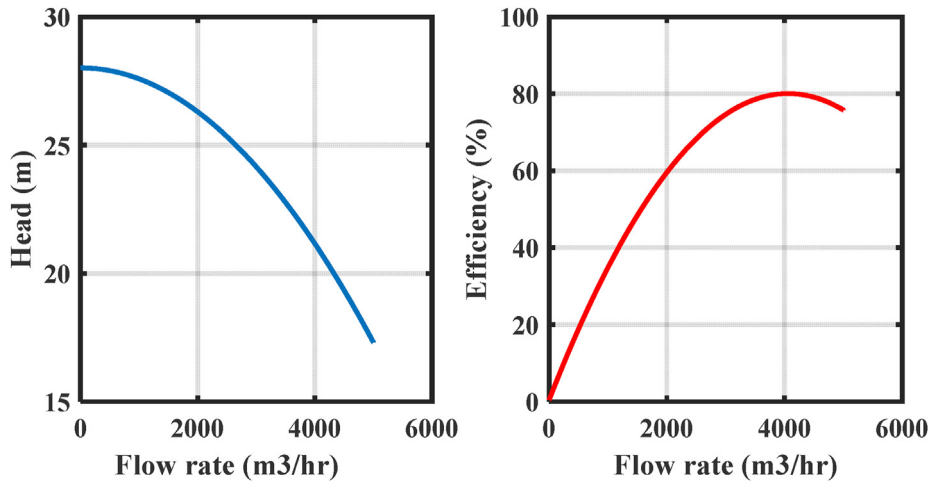**Figure 16.** Toronto water network.

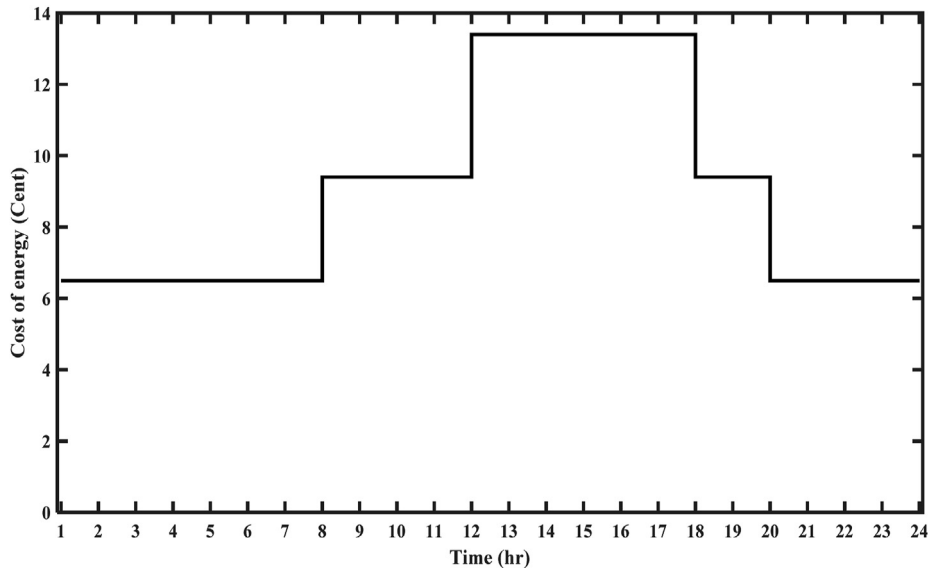**Figure 17.** The characteristic curves of Toronto WDN pumps.

Figure 18. Ontario daily energy tariff.

away from each other and this law is called coulomb' 1st law [26]. The magnitude of this force (F) depends on the values of these two charges (Q_1 and Q_2) and the square of distance (d) between them. The coulomb' 2nd law states that F is proportion to $Q_1 \times Q_2$ and $1/d^2$ [26].

On the other hand, the Newton 2nd law is used to describe effects of this generated force on the motion velocity of these charges.

The AEFA has agents and strength like optimization algorithms. The number of charges represent the agents, the magnitude of the charge equivalents its strength that is represented in met-heuristic techniques and values of this charge equivalent the strengths. The generated attraction forces between them achieve the motion control of these charges. Where the big magnitude charge (best local fitness) attracts to its position the small magnitude charges. The optimal solution is represented by the best position of these charges in the search space [26].

To formulate this algorithm to be used as an optimization algorithm, suppose that any charge (Q_i) has a position (X_i) in a multi-dimension search space and this position is defined by $X_i = (x_i^1, x_i^2, x_i^3, \ldots, x_i^n)$. The position of the charge is updated depending on its local best fitness as follow [26]:

$$p_i^n(t+1) = \begin{cases} p_i^n(t) & \text{if } f(p_i(t)) < f(X_i(t+1)) \\ x_i^n(t+1) & \text{if } f(X_i(t+1)) \leq f(p_i(t)) \end{cases} \tag{12}$$

where P_i is the position of local best particle and p_i^n is the position of global best particle.

The local fitness of a charge has an effect on the adjacent charge by the generated force between them that is calculated by:

$$F_{ij}^n(t) = K(t) \frac{Q_i(t) * Q_j(t)\left(p_i^n(t) - X_i^n(t)\right)}{R_{ij}(t) + \varepsilon} \tag{13}$$

where

$K(t)$: a time varying variable called coulomb constant,
ε: a correction positive constant,
t: the time in seconds in continuous process and it represents the samples or steps in discrete process
R_{ij}: the spacing between the charges and can be determined using Euclidian equation as follow [26]:
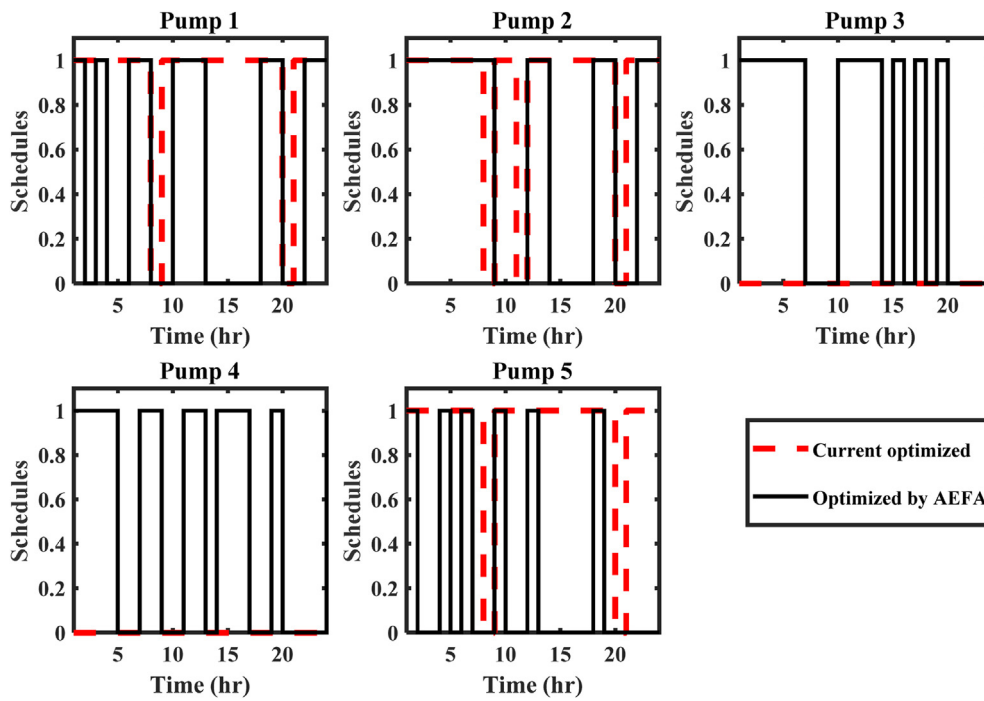
Figure 19. The scheduling of part of Toronto WDN pumps.
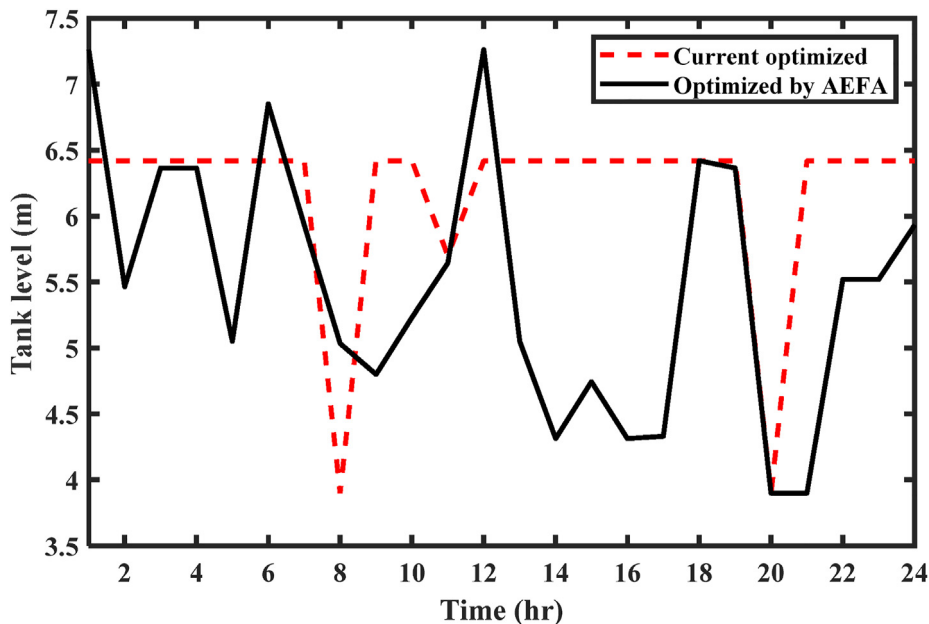
Figure 20. Water level of Toronto WDN tank.

$$R_{ij}(t) = \left\| X_i(t), \ X_j(t) \right\| \tag{14}$$

The constant $K(t)$ is calculated as a function of iteration and the maximum iteration as:

$$K(t) = K_0 * \exp\left(-\alpha * \frac{iter}{iter_{max}} \right) \tag{15}$$

where

K_0: K initial value,
α: constant,
$iter$: value of iteration
$iter_{max}$: iteration maximum number.

The charge Q_i is affected by the forces of all adjacent charges and the effect of these forces is calculated by:

$$F_i^n(t) = \sum_{j=1, \ j \neq i}^{N} rand() * F_{ij}^n(t) \tag{16}$$

This problem is converted to be stochastic by adding *rand ()* factor in Eq. (16) and its value is random between 0 and 1.

This charge Q_i constructs an electric field (E) around it in all dimensions and this electric field can be calculated in any dimension n at any time t using the following equation:
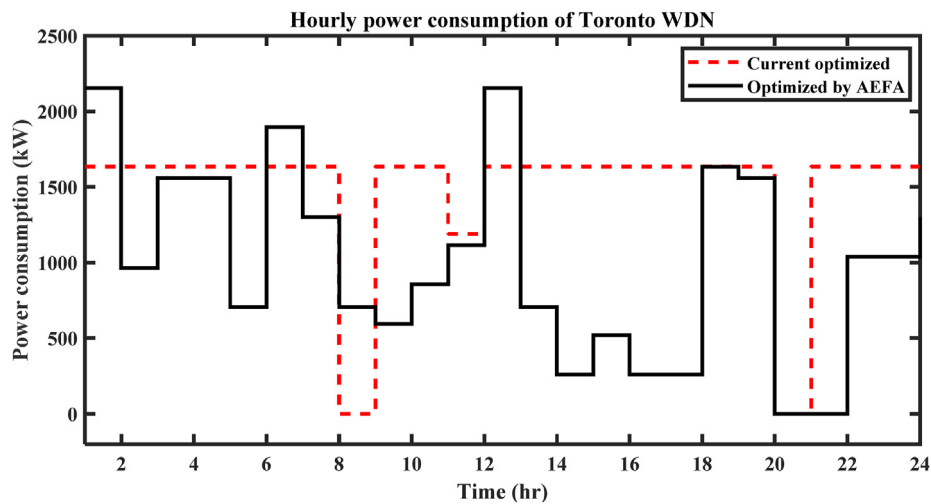
Figure 21. The daily power consumption of Toronto water pump station.

Table 9. Results of Toronto water network.

	Current optimized scheduling	Optimized scheduling by AEFA
Energy cost (f_1) ($)	2935.7	1826.54
Demand charges (f_2) ($)	254	211
Maximum number of switching for all pumps	13	41
Maintenance cost (f_3) ($)	20.5	6.5
Total cost ($)	3,210.2	2044.04

Table 10. Comparison between GA, PSO and the proposed AEFA for Toronto WDN.

Algorithm	No of generation\iteration	Objective function	Percentage cost saving
GA	45	2070.5	35.5 %
PSO	40	2090.9	34.5 %
AEFA	18	2044.04	36.3 %

Figure 22. The convergence comparison of AEFA with GA and PSO for Toronto WDN.

$$E_i^n(t) = \frac{F_i^n(t)}{Q_i(t)} \tag{17}$$

The effect of attraction force stated in Eq. (16) reveals in giving an acceleration in n^{th}-dimension to this charge and this acceleration is calculated by:

$$a_i^n(t) = \frac{Q_i(t)^*E_i^n(t)}{M_i(t)} \tag{18}$$

where $M_i(t)$: the charge mass at time t.

This acceleration changes the velocity of charge using the newton 2nd law as follow:

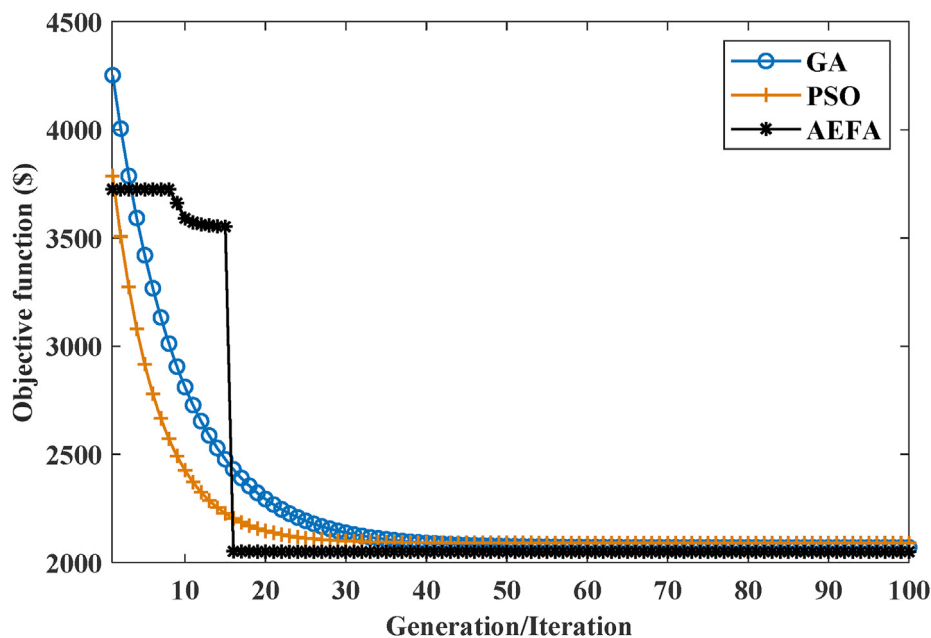$$V_i^n(t+1) = rand()^*V_i^n(t) + a_i^n(t)^*\Delta t \tag{19}$$

And this change of velocity changes also the charge position and the updated position is determined by:

$$X_i^n(t+1) = X_i^n(t) + V_i^n(t+1)^*\Delta t \tag{20}$$

The charge of greatest magnitude (normalized $Q_{best} = 1$) represents the optimal solution best fitness and the fitness of other charges is in between 0 and 1. The magnitude of charge of best fitness value is calculated by:

$$Q_i(t) = \frac{q_i(t)}{\sum_{i=1}^{N} q_i(t)} \tag{21}$$

where $q_i(t)$ is calculated by:

$$q_i(t) = \exp\left(\frac{fit_i - worst(t)}{best(t) - worst(t)}\right) \tag{22}$$

where

fit_i: the charge best fitness,

$best(i)$ and $worst(i)$: represent best and worst solutions, respectively and their values depend on the objective function type as follow: the depend on the type of the optimization problem; maximization or minimization.

If the objective function is to fulfil the maximum solution than:

$$best(t) = \max\left(fit_j(t)\right), \quad j \in (1, 2, \ldots, N) \tag{23}$$

$$worst(t) = \min\left(fit_j(t)\right), \quad j \in (1, 2, \ldots, N) \tag{24}$$

While if the objective function is to fulfil the minimum solution than:

$$best(t) = \min\left(fit_j(t)\right), \quad j \in (1, 2, \ldots, N) \tag{25}$$

$$worst(t) = \max\left(fit_j(t)\right), \quad j \in (1, 2, \ldots, N) \tag{26}$$

From the previous explanation of AEFA, it is clear that AEFA is a population based algorithm and the optimal solution is obtained by the particles motion like PSO but AEFA has different aspects that are not found in PSO:

  i) AEFA uses the laws of Coulomb that is used to show the relations between electric charges whereas PSO mimics the behavior of bird's motion
  ii) Direction of particle movement in AEFA is determined by the forces effect of the near particles whereas in PSO, it is determined by best position locally and globally.
  iii) The value of objective function has an effect on solution updates in AEFA whereas it does not an effect in PSO.
  iv) AEFA uses small number of parameters to control the process in comparing with PSO.

3.2. Implementation of the proposed algorithm

This work is a combined process between the EPANet hydraulic simulator and the proposed optimization algorithm. The optimization algorithm is used to fulfil the objective function and some of its constraints by generating different pump schedules and the hydraulic simulator is used to assess the feasibility of theses scheduling and to fulfil some objective function constraints that depend on hydraulic process such as the minimum and maximum required pressure limits at the demand nodes, the total combined water capacity and the tanks limit. The solution of this problem is a combination of binary number solution that represents the decisional variables or position of particles (X_1, X_2, ..., X_{np}). The values of each digit is zero or one where zero represents that the pump state is off and one represents that the pump state is one.

Step #1: initialize the parameters of the proposed optimization algorithm; search space, number of particles, start positon, start velocity, K_0 and α.

Step #2: generate a set of pump schedules.

Step #3: run the hydraulic simulator to evaluate the feasibility of the schedules and to ensure the fulfil of the hydraulic constraints.

Step #4: calculate the local best feasible fitness that represents the charges mass.

Step #5: repeat the process starting from step #2 till reaching to the maximum iteration.

Step #6: select the global best feasible objective function (*fit*) and its pump schedules.

The flowchart of the combined methodology of AEFA and EPANet simulator to find the optimal water pump scheduling in a water network is Figure 2.

4. Experimental results and discussion

In this work, three water networks are tested. These networks are EPANet practical example network, Richmond network and a part from Toronto network.

The optimal scheduling is conducted based on three different energy tariffs. The matlab programming environment is used to model this methodology with the help of EPANet matlab toolkit [27]. The c_m is the penalty for a single pump switch and this value is given in [28]. The used EPANet software version is EPANET 2.0.12.

In all tested networks, there is an initial quantity of water stored in the tank (prior to the simulation) that will reach the consumer without pumping and once the water level in the tank becomes the lower than the head required by the consumer, the water reaching the consumer has to be pumped.

4.1. EPANet Net3 water network

EPANet Net3 water network is an EPANet example and it is fed by two water sources. This network contains three elevating tanks, one-hundred and twenty pipes, ninety-four nodes, and two pumping stations with labels pump 10 and pump 335 as shown in Figure 3 [29]. The characteristic curves of these pumps are shown in Figure 4. In this network, EPANET will consider a constant value of the efficiency for all flow rates regardless the operation of all pumps or any combination of them.

The upper and lower limits of the tank levels are illustrated in Table 1. The minimum and maximum value of combined water volume $\pm$ 10 % and the maximum number of switching on/off of pumps is 5. Also, the demand and the minimum required pressure and head at all networks node are given in [30].

In this network, the used energy consumption is two rates tariff as follows:

- Off-peak tariff = 0.0244 $/kWh for two time intervals; from 00 am to 7 am and from 10 pm to 00 am.
- Peak tariff = 0.1194 $/kWh for the time interval from 7 am to 10 pm.

The coulomb constant K_0, shown in Eq. (15), has an effect on the performance of AEFA where the results of studying this effect are shown in Figure 5. As shown in Figure 5, the value of K_0 that gives minimum number of iterations, eleven iterations, and best solution is 200 with α = 30.

The results of applying the proposed methodology for optimal water pumping are compared with the current optimized schedules [29]. Figure 6 shows the pump schedules that is checked for hydraulic feasibility using EPANet simulator and it is clear that the proposed methodology prevents the switching on of the pumps during the highest energy price rates as maximum as it can. The water level in the tanks is shown in Figure 7 and it shown that the ware level in all tanks is within the limits that are stated in Table 1. The profile of power consumption of all network pumps is shown in Figure 8.

The results in Table 2 show that the cost of the energy consumption has the big contribution in comparing with other costs; demand charge and maintenance cost. The demand charge and maintenance costs have small contributions that are 9.63 % and 10.24 % for the current optimized scheduling and optimal scheduling by AEFA, respectively. The cost of this daily energy consumption is calculated and it is found that the cost of energy consumption decreased from 1367.3$ to 1115.5$ with daily cost saving 18.4%.

To evaluate the performance of AEFA, a comparison with the genetic algorithm and the particle swarm optimization is conducted using the same energy consumption rates. The selected parameters of GA are: population size = 100, number of generation = 100 and mutation probability = 0.167. While the PSO parameters are: population size = 100, acceleration constants = 2 and number of iterations = 100. The results shown in Figure 9 depict that the AEFA needs 11 iterations to reach to its minimum value of objective function and AEFA fulfils the maximum saving in comparing with the other optimization algorithms as shown in Table 3.

4.2. Richmond water network

Richmond water network (WDN) is a real network available in UK [31]. It contains one water source, seven pumps, six tanks, forty-four pipes and forty-seven nodes as shown in Figure 10. The rating and water flow of these pumps are shown in Table 4. The characteristic curves of these pumps are shown in Figure 11 and a constant value of the efficiency for all flow rates is considered regardless the operation of all pumps or any combination of them. The upper and lower tank levels are depicted in Table 5. The minimum and maximum value of the combined water volume is ± 10 % and number of allowable switching on/off of pump limits is 6. This network is tested using the variable energy tariff that is shown in Table 6 where the peak period starts from 7 am to 00 am [31]. Also, the demand and the minimum required pressure and head at all networks node are given in [31].

For this water network, the AEFA is trained using different values of K_0, the best value of K_0 is 500 with α equals 28, and the optimum value of objective function is achieved after twenty-three iterations.

Applying the proposed strategy changes the pumps switching on/off to fulfil the minimum energy consumption cost with all constraints within limits. The pumps scheduling is shown in Figure 12, the tanks water level is shown in Figure 13, and it is obvious that the level of water in tanks does not violate the limits that are given Table 5.

The daily power consumption of this network is shown in Figure 14 and the cost of energy consumptions per 24 h of the network pumps is decreased from current optimized value [32], 2,836.2 £, to 2,394.2 £. This optimal scheduling achieves a cost saving of 15.6 % as shown in Table 7. As depicted also in Table 7, the costs of maintenance and

represent 9.75 % and 10.35 % of the energy consumption for the current optimized scheduling and the optimal scheduling by AEFA.

For this water network, a comparison with GA and PSO is also conducted to assess the performance of AEFA. The results show that the minimum value of objective function is fulfilled by AEFA, as depicted in Table 8, and AEFA is faster than GA and PSO as shown in Figure 15.

4.3. Toronto water network

The Toronto water network is a very large, as shown in Figure 16, and a part of it is studied. This part contains five pumps and one water tank. The upper and lower limits of water level in this tank are 9.1 m and 1.2 m, respectively. The minimum and maximum values of the combined water volume are 2400 and 18200 m³, respectively. The maximum and minimum number of switching on/off of pumps are 0 and 4, respectively [33]. All pumps have the same characteristic curve that is shown in Figure 17. Also, the demand and the minimum required pressure and head at all networks node are given in [34].

The Ontario variable daily energy consumption rates that are used in this network are shown in Figure 18 [35]. Where the energy rate is very high, 13.4 cents/kWh, in the period of 12 pm–6 pm, moderate rate, 9.4 cents/kWh, in periods 7 am to 12 pm and 6 pm–8 pm and the lowest rate is 6.5 cents/kWh in the period 8 pm to 8 am.

The training of AEFA found that the best value of K_0 is 500 and it gives the best fitness after 18 iterations. Figure 19 shows the schedules of water pumps and this schedules maintain the water level in tanks to be within the limits as shown in Figure 20. The daily energy consumption of this network is depicted in Figure 21. This optimized schedules also decrease the cost of energy consumption of this water station from its current value, 3,210.2 $, to 2,044.04 with a percentage cost saving equals to 36.3 %. The costs of maintenance and demand have a small contribution in the total cost and they are 9.35 % and 11.9 % for the current optimized scheduling and the optimal scheduling using AEFA, respectively, as shown in Table 9.

Also a comparison between the proposed AEFA and GA and PSO is conducted. The results in Table 10 depicts that the AEFA achieves the maximum cost saving with a percentage of 36.3 % and also AEFA is very fast in comparing with GA and PSO as shown in Figure 22 where AEFA reaches the minimum value of objective function after 18 iterations.

With the aforementioned advantages of AEFA comparing with GA and PSO, there are weaknesses of this algorithm, as with any metaheuristic algorithm, such as local minima stagnation and poor exploration capability. Also regarding the application of AEFA in solving optimal scheduling of WDN, AEFA is used to schedule the operation of fixed speed pumps and cannot be used in case of variable speed pumps or parallel operation of pumps.

5. Conclusions

This paper proposes a solution to reduce the cost of energy consumption of water networks by optimal on/off control of water pumps. The proposed solution is a hybrid process from optimization algorithm and a hydraulic simulator. The optimization algorithm is the modern artificial electric field algorithm that is used to generate different schedules. The EPANet hydraulic simulator is used to check the hydraulic feasibility of these schedules and to ensure also these schedules fulfil the hydraulic constraints such as water tanks level and the water nodes pressure. The objective function of this work is to minimize the cost of energy consumption, the demand charge and cost of pumps maintenance by decreasing the number of switching on/off. This hybrid methodology is applied on three different water networks such as EPANet example network, Richmond network in UK and a part of Toronto water network with three different variable energy tariffs. The Matlab software is utilized to model these networks and to help in finding the optimal schedules. For each water network, the AEFA is tested to obtain perfect values of its controlling parameters. The results show that applying the hybrid

methodology decreases the cost of energy consumption of these water networks with fulfilling the hydraulic constraints. Also AEFA is compared with other optimization algorithms such as the genetic and particle swarm algorithms on the same networks and energy tariff and the results show the superiority of AEFA in the convergence and saving of the cost of energy consumption.

Declarations

Author contribution statement

Abdelazeem A. Abdelsalam: Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Hossam A. Gabbar: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

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Additional information

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