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An enhanced binary dragonfly algorithm based on a V-shaped transfer function for optimization of pump scheduling program in water supply systems (case study of Iran)

Jafar Jafari-Asl [a], Gholamreza Azizyan [a,*], Seyed Arman Hashemi Monfared [a], Mohsen Rashki [b], Antonio G. Andrade-Campos [c]

[a] *Department of Civil Engineering, Faculty of Engineering, University of Sistan and Baluchestan, Zahedan, Iran*
[b] *Department of Architecture Engineering, Faculty of Arts and Architecture, University of Sistan and Baluchestan, Zahedan, Iran*
[c] *Centre for Mechanical Technology & Automation, GRIDS Research Group, University of Aveiro, Campus Universitário de Santiago, 3810-193 Aveiro, Portugal*

A R T I C L E I N F O

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Binary dragonfly algorithm
Water supply system

A B S T R A C T

With the continual growth of population and shortage of energy resources, the optimal consumption of these resources is of particular importance. One of these energy sources is electricity, with a significant amount being used in pumping stations for water distribution systems (WDS). Determining the proper pumping schedule can make significant savings in energy consumption and particularly in costs. This study aims to present an improved population-based nature-inspired optimization algorithm for pumping scheduling program in WDS. To address this issue, the binary dragonfly algorithm based on a new transfer-function coupled with the EPANET hydraulic simulation model is developed to reduce the energy consumption of pumping stations. The proposed model was firstly implemented and evaluated on a benchmark test example, then on a real water pumping station. Comparison of the proposed method and the genetic algorithm (GA), evolutionary algorithm (EA), ant colony optimization (ACO), artificial bee colony (ABC), particle swarm optimization (PSO), and firefly (FF) was conducted on the benchmark test example, while the obtained results indicate that the proposed framework is more computationally efficient and reliable. The results of the real case study show that while considering all different constraints of the problem, the proposed model can decrease the cost of energy up to 27% in comparison with the current state of operation.

1. Introduction

A significant amount of the annual operating costs of water distribution systems (WDS) is related to the operation of pump stations. In a study by Savic et al. [1], the cost of pumping in the United Kingdom for a one-year period was estimated at about £ 700 million. Therefore, it is possible to determine the appropriate time-table for water supply pumping stations to decrease the costs. Indeed, minimizing the costs of operating pumping stations, while satisfying the allowable tank water levels, is considered the main objective of the pump scheduling program [2,3]. However, finding optimal pump schedules is a complex task due to the complexity, and large-

* Corresponding author.
E-mail address: G.azizyan@eng.usb.ac.ir (G. Azizyan).

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scale size of WDS, the high variation in demand multiplier patterns and the complexity of energy tariffs. Therefore, this issue has attracted researchers' ideas for several years. The problem of optimizing the pump scheduling is mathematically a large-scale nonlinear mathematical problem because the objective function and the constraints are nonlinear with a high number of decision variables[4].

Previously, researchers have used traditional optimization methods such as linear programming [5], nonlinear programming [6,7], and dynamic programming [8,9] to optimize the pump scheduling program. In the last two decades, metaheuristic optimization methods have been developed and widely used to solve complex engineering problems [10–12]. The advantages of these methods are their simplicity and flexibility, even in complex issues. Another advantage of these methods, compared with the traditional methods, is that these algorithms prevent trapping in a local minimum in the search space by using some specific mechanisms. In other words, these algorithms combine local search and global search patterns [13].

In recent years, many efforts have been made to use metaheuristic algorithms such as genetic algorithm (GA), simulated annealing (SA), ant colony optimization (ACO), and harmony search (HS) to solve the problem of optimizing pump schedules. For example, Mackle et al. [14] proposed a genetic algorithm to determine the timing of optimal pump operation to minimize operating costs as an objective function, and by solving a simple example, they showed that the genetic algorithm yields acceptable results. Rodin & Moradi-Jalal [15] developed a model based on the GA to optimize the operation of a multi-pump pumping station in a real urban WDS with an objective function of minimizing the operating costs during a 24 h. They showed that the genetic algorithm has a desirable capability in real-world issues. Van Zyl et al. [16] conducted a study on the optimal utilization of pumping stations to minimize the cost of energy using a hybrid GA with a hill climber algorithm (HCA). They used a GA to find the global search space and the HCA to search for the optimal local space. In their study, they used an implicit setup method to control the water level of the tank to provide pump schedules.

Moreover, several studies have been conducted to reduce the energy consumption of pumping stations on multi-objective optimization by using meta-heuristic algorithms. One of these studies is the study of López-Ibáñez et al. [17], which used the strength Pareto evolutionary algorithm (SPEA2) to optimize the multi-objective pump scheduling with the objective functions of minimizing energy and maintenance costs. Makaremi et al. [18] developed a self-Adaptive NSGA-II to reduce the energy cost and the number of switching pumps during an optimal time interval. Prominent metaheuristic algorithms such as GA, PSO, HS, and ACO have been used to solve the optimal pump scheduling problem. Dai and Tinh [19]; Savsani et al. [20]; Turci et al. [21]; Patel and Rajs [22]; Cimorelli et al. [23] and Androutsopoulos et al. [24] are a series of studies that investigated the optimization pump scheduling program as a single or multi-objective problem utilizing meta-heuristic algorithms. However, the evaluation and application of emerging optimization algorithms in this problem are of particular importance.

One of these emerging algorithms is the dragonfly algorithm (DA), inspired by dragonfly behavior, to solve continuous optimization problems [25–27]. DA makes better performance compared to some other algorithms [28] due to its efficiency and accuracy. Based on the no free lunch (NFL) theory, no metaheuristic algorithms can solve all optimization problems. Moreover, the DA cannot be directly used for pump scheduling problems since this problem is with binary solution spaces. Therefore, it is necessary to convert the DA to a binary version algorithm to make it usable for pump scheduling problems. Also, a literature review shows that DA has not been applied so far for such problems.

One of the most common methods for converting the conventional optimization algorithms to binary solution space is the use of transfer functions (TF). Choosing a suitable TF has a significant impact on the increased accuracy and performance of velocity-based binary algorithms (e.g., PSO and DA). Therefore, the two main contributions of this study are outlined as follows:

1. A metaheuristic algorithm, namely Dragonfly Algorithm (DA) with a new TF is used for optimal operation of the pumping station in WDS, programmed in MATLAB and integrated with the EPANET hydraulic simulation model.
2. We investigated a comparative analysis to evaluate the effect of several new transfer functions on the binary version of DA to find the optimal pump scheduling program to reduce energy consumption cost.

2. Methodology

2.1. Optimization model

2.1.1. Dragonfly algorithm

The Dragonfly algorithm was first introduced by Mirjalili. [27] based on the dynamic and static swarm behaviors of dragonflies to solve optimization problems. In the static swarm, dragonflies form subgroups, fly into different spaces that are the main target of the exploration phase.

While in the dynamic swarm, dragonflies fly in larger populations along with a unit that is the same phase of exploitation. Influential factors in updating the sample location by considering the behavior of the swarm are independence (S_i), alignment (A_i), cohesion (C_i), access to the source of food (F_i), and distance from the enemy (E_i), respectively, which are mathematically modeled as following [29–31]:

$$S_i = -\sum_{j=1}^{N} X - X_j \tag{1}$$

Table 1
S-shaped and V-shaped transfer functions.

Name	Equation	Type
TF_1	$TF_1(\Delta X) = \frac{1}{1+e^{-2\Delta X}}$	S-shaped
TF_2	$TF_2(\Delta X) = \frac{1}{1+e^{-\Delta X}}$	S-shaped
TF_3	$TF_3(\Delta X) = \frac{1}{1+e^{(\frac{-\Delta X}{2})}}$	S-shaped
TF_4	$TF_4(\Delta X) = \frac{1}{1+e^{(\frac{-\Delta X}{3})}}$	S-shaped
TF_5	$TF_5(\Delta X) = \left\lvert\tanh(\frac{\Delta X}{2})\right\rvert$	V-shaped
TF_6	$TF_6(\Delta X) = \lvert\tanh(\Delta X)\rvert$	V-shaped
TF_7	$TF_7(\Delta X) = \left\lvert\frac{\Delta X}{\sqrt{\Delta X^2+1}}\right\rvert$	V-shaped
TF_8	$TF_8(\Delta X) = \left\lvert\frac{2}{\pi}\arctan(\frac{\pi}{2}\Delta X)\right\rvert$	V-shaped

$$A_i = \frac{\sum_{j=1}^{N} V_j}{N} \tag{2}$$

$$C_i = \frac{\sum_{j=1}^{N} X_j}{N} - X \tag{3}$$

$$F_i = X^{+} - X \tag{4}$$

$$E_i = X - X \tag{5}$$

In all of the above equations, X is the current position of the dragonfly, X_j is the jth neighbor of the dragonfly, N is the number of neighboring dragonflies, V_j represents the velocity jth of the neighboring dragonfly, $X^{+}$is the position of the food source, and X^{-}represent the enemy's position. To update the position of the dragonflies in a search space and simulate their movements, the step vector (ΔX) and location (X) is considered and defined as:

$$\Delta X_{t+1} = (sS_i + aA_i + cC_i + fF_i + eE_i) + w\Delta X_t \tag{6}$$

where a is the coefficient of fundamental motion, c is the coefficient of cohesion, f is the source of food, e represents the enemy's coefficient, w is the coefficient of inertia, and t is the number of iterations. According to the above-mentioned coefficients during optimization that initialize randomly, it is possible to obtain various exploratory and operational behaviors. After calculating the step vector, the position vector is also obtained as:

$$x_{t+1} = x_t + \Delta x_{t+1} \tag{7}$$

Suppose there are no neighbors to further improve the random and exploratory behavior of dragonflies. Therefore, it is necessary to fly them around the search space using a random walk. This assumption is applied by using equations (8) to (10):

$$x_{t+1} = x_t + l\grave{e}vy(d) \times x_t \tag{8}$$

In Eqs. (8)–(10), t is the current repeat number, and d is the position vector, and the value (Le`vy) is calculated by:

$$l\grave{e}vy(x) = 0.01 \times \frac{r_1 \times \sigma}{|r_2|^{\frac{1}{\beta}}} \tag{9}$$

r_1 and r_2 are two random numbers in the interval [0, 1] and $\beta$the constant value (which in this work is equal to 1.5). The value of $\sigma$is calculated by the following equation:

$$\sigma = \left(\frac{\Gamma(1+\beta) \times \sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right) \times \beta \times 2^{\left(\frac{\beta-1}{2}\right)}} \right)^{\frac{1}{\beta}} \tag{10}$$

where $\Gamma(x) = (x-1)!$

To update the position X and ΔX in the vicinity of each dragonfly, the Euclidean distance method is used, which calculates the distance between two points based on the Pythagorean Theorem among all dragonflies and choosing N of them. Updating continues until the final criterion is reached.

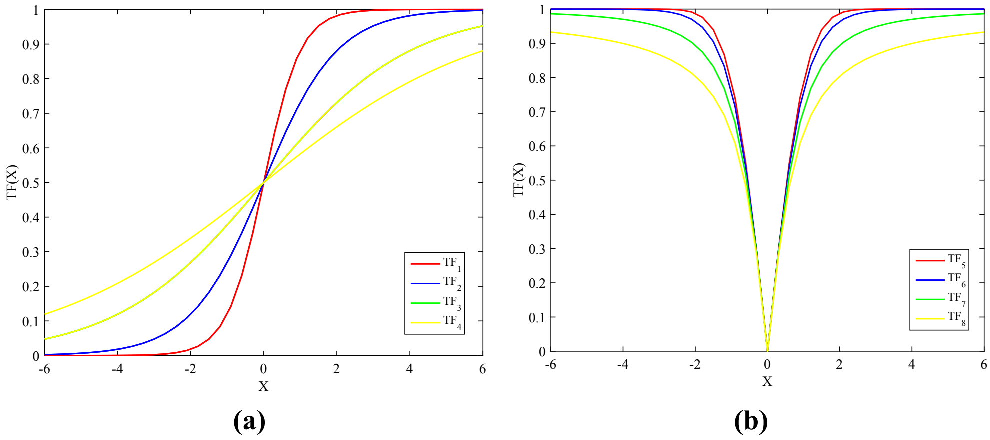

Fig. 1. Sample S-shaped and V-shaped transfer functions; (a) S-shaped transfer and (b) V-shaped transfer functions.

2.1.2. The proposed binary dragonfly algorithm

Given that optimization is different in the binary search space compared to the continuous space, the simplest method for converting continuous algorithms to a binary algorithm without modifying its structure is the application of a transfer function [32]. The transfer function receives the velocity value (step length) as an input and returns a number in the range of [0 or 1], which expresses the possibility of changing situations. The output of this function is proportional to the velocity value. Therefore, the large velocity of the search agent makes it likely to update its position. The S- and V-shaped TFs are presented in Table 1 and Fig. 1, respectively, which are widely used to convert the continuous space into binary.

The TF_7 (Eq. (11)) used in the original version of BDA to convert the continuous space of the dragonfly algorithm into a binary space algorithm is the following:

$$T(\Delta X) = \left| \frac{\Delta X}{\sqrt{\Delta X^2 + 1}} \right| \tag{11}$$

The new position of the particle is updated through

$$X_{t+1} = \begin{cases} \neg X_t & r < T(\Delta X_{t+1}) \\ X_t & r \geq T(\Delta X_{t+1}) \end{cases} \tag{12}$$

where r is a number in [0, 1].

The flowchart of the BDA algorithm is presented in Fig. 2.

The present study will evaluate all the TFs provided in Table. 1 to convert the search space to solve the optimal pump scheduling problem.

2.1.3. Optimization problem of pump scheduling program

2.1.3.1. Objective function. The main goal of optimizing the pump scheduling program is for reducing the total energy costs $C_E(s)$, which consist of two parts: the energy consumption (C_D) and the charge demand (C_C) [18]. Thus, the optimization problem can be described mathematically as follows:

$$\begin{aligned} & Minimize f(\boldsymbol{X}), \boldsymbol{X} = \begin{bmatrix} x_1^1, x_2^1, \cdots, x_{NT}^1 \\ x_1^2, x_2^2, \cdots, x_{NT}^2 \\ \vdots \\ x_1^n, x_2^n, \cdots, x_{NT}^{NP} \end{bmatrix}_{NP \times NT}; \\ & Subjectto: \\ & l_k(\boldsymbol{X}) = 0, k = 1, \cdots, w; \\ & g_j \leq 0, j = 1, \cdots, m; \end{aligned} \tag{13}$$

where $\boldsymbol{X}$ is a vector of the decision variables, h_k and g_j are the constraints. $f(\boldsymbol{X})$ is the objective function that is calculated by using Eq. (14) as follows:

$$C_E(s) = C_D + C_c \tag{14}$$

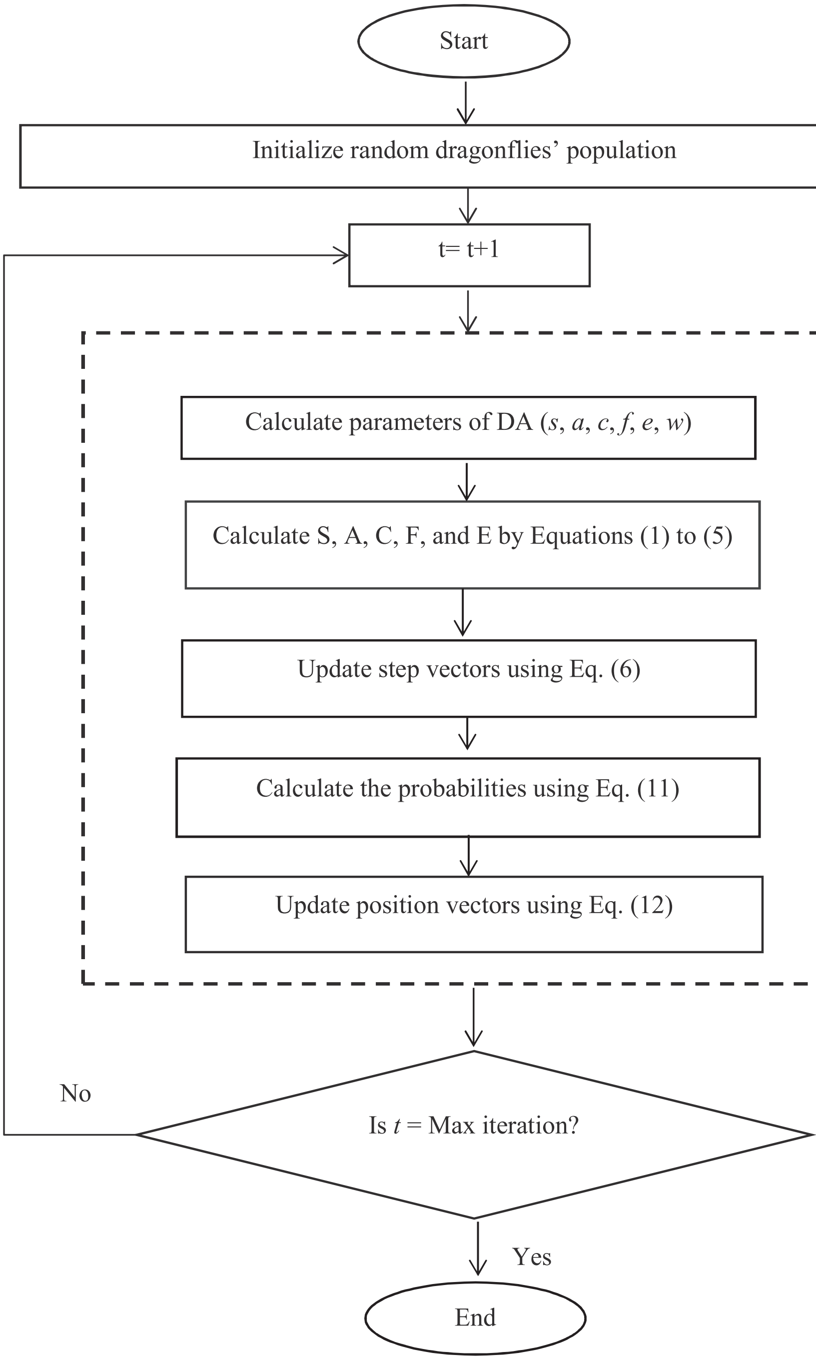

Fig. 2. Flowchart of BDA.

In which

$$C_D = \sum_{n=1}^{NP} (P_D \times E_D(n)) \tag{15}$$

$$C_c = \sum_{n=1}^{NP} \sum_{t=0}^{NT-1} (P_c(t) \times E_c(n,t) \times S(n,t)) \tag{16}$$

where *S(n, t)* is the duration for which pump *n* is operating during the time interval *t* (hour), P_c (*t*) is the energy consumption during the time interval t (\$/kWh), $E_C(n, t)$ is the energy consumption rate of pump n during time interval t (kWh/h), P_D is the demand charge (\$/kW), and $E_D(n)$ is the maximum electric power consumption of pump n (kW).

It should be noted that for each time interval, the energy consumption per pump depends on the flow rate, the total dynamic head, and the efficiency with which it operates can be formulated as follows:

$$E_c(n,t) = \frac{10^{-3}.\gamma.Q(n,t)h(n,t)}{e(n,t)} \tag{17}$$

where γ is the specific weight of water, $e(n, t)$ is the efficiency of pump n during the time interval t, and 10^{-3} is to convert the energy rate to kWh/h. Also, the maximum electrical power of pump n, $E_D(n)$, during period NT is obtained by substituting the peak discharge through the pump and the corresponding dynamic head into Eq. (17).

2.1.3.2. Constraints. In general, three types of constraints are imposed on the pump scheduling optimization problem. The first type of constraints is the continuity law (18) and the energy conservation law (18), which are automatically controlled by the EPANET hydraulic simulation software [18,33].

$$\sum Q_{in,i} - \sum Q_{out,i} = 0 \tag{18}$$

$$H_{i,t} - H_{j,t} = h_{ij,t} \tag{19}$$

$$h_{ij,t} = \frac{10.668 L_{ij} Q_{ij,t}^{1.852}}{C_{ij}^{1.852} d_{ij}^{4.871}} \tag{20}$$

where, $Q_{in,i}$ is the input flow to node i, $Q_{out,i}$ is the output flow of node i, $H_{i,t}$ is the head in node i, $H_{j,t}$ is the head in node j, $h_{ij,t}$ is the head loss between the nodes i and j, C_{ij} is the Hazen-Williams constant, d_{ij} is the pipe diameter and L_{ij} is the length of the pipe between nodes i and j.

Secondly, to supply the pressure heads at the demand nodes, the following constraint must be met.

$$g_{i,t} = H_i^{min} - H_{i,t} \leq 0 i = 1, \cdots, nn \tag{21}$$

where, H_i^{min} is the minimum pressure head required to supply the demand in the ith node,

Another type of constraint is related to storage tanks. These assertions state that the level of water tanks during the operation period should not exceed the maximum and minimum capacity of the tank.

$$l_{k,t} = y_{Fin,k} - y_{Ini,k} = 0 k = 1, \cdots, K \tag{22}$$

$$g_{k,t} = y_k^{min} - y_{k,t} \leq 0 k = 1, \cdots, K \tag{23}$$

$$g_{k,t} = y_{k,t} - y_k^{max} \leq 0 \tag{24}$$

where, $y_{Ini,k}$ is the level of water at the beginning of the operation period in the tank k, $y_{Ini,k}$ is the level of water at the beginning of the operation period in the tank k, y_k^t is the water level at time t in the tank k, $y_{Min,k}$ is the minimum allowable water level in tank k, $y_{Max,k}$ is the maximum allowable water level in tank k, and$t$ is the time step, in hours, throughout 24 h.

2.1.3.3. Decision variables. Here, the optimization decision variables are a sequence of binary integer numbers, i.e., 0 and 1, the former indicating that the pump is off and the latter indicating that it is on during the operation period.

2.1.4. Framework of the proposed model

The framework of the simulation–optimization model is consisting of two parts as I) Utilizing the BDA to find the optimal scheduling program of the pumps; II) Utilizing the EPANET software for the hydraulic analysis and calculate the objective function and constrains violations. Thus, the followed steps of the proposed simulation–optimization can be summarized as:

Step 1: Initialize the setting parameters of DA, including the number of population size and the maximum iterations.
Step 2: Initialize the dragonflies' population and step vectors using Eq.6.
Step 3: Run the simulation model and calculate the objective function.
Step 3: Checking and handling the constraints violations by applying the penalty function method:
While the end condition is not satisfied
Calculate the objective values of all dragonflies;
Update the food source and enemy;
Update w, s, a, c, f, and e;
Calculate *S, A, C, F,* and E using Eqs. 1–5;
Update the step vectors using Eq. (6);
Calculate the probabilities using a TF;

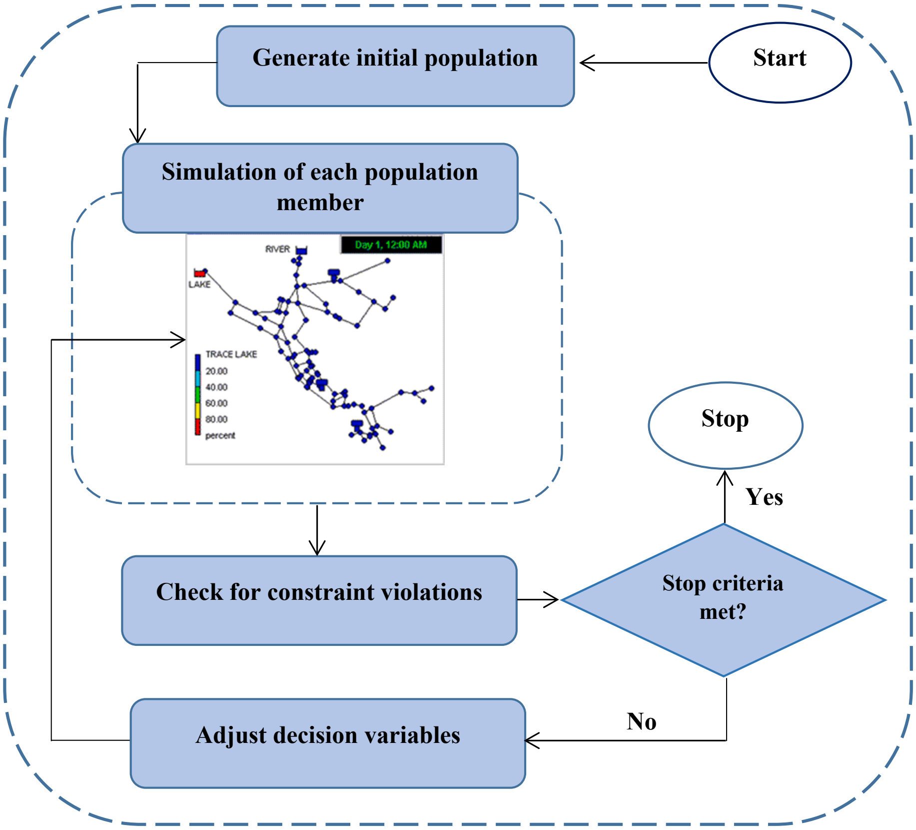

Fig. 3. The Simulation-optimization procedure of the problem.

Update the position vectors using Eq. (12).
End while
Step 4: Report the optimal pump scheduling program.
Fig. 3**.** shows the structures of the Binary Dragonfly Algorithm coupled with the EPANET hydraulic simulation and their connections.

3. Case studies

3.1. Case study I

The water distribution system considered in the first case study was introduced by Van Zyl et al. [16]. This water distribution system has a main reservoir with a constant water level, three pumps, two storage tanks, one control valve, and two demand nodes (Fig. 4). Pumps I and II work to pump the water from the main reservoir to the network in a parallel form. Pump III also conveys water from reservoir A to reservoir B. The 24-hour pump-scheduling period is with different hourly tariffs, and nodes 5 and 6 are demanding nodes. More details of the case study I are presented in Fig. 5 and Table 2, and Table 3. [16,34].

3.1.1. Results and discussion

The developed BDA-based simulation–optimization model with different TFs was evaluated to determine the optimal operation plan for Van Zyl water network pumping stations. BDA is a metaheuristic algorithm, and the optimal solution can be obtained if the appropriate values are determined for the adjustable parameters of the algorithm. Consequently, the best values of parameter B, population number, and maximum iteration were obtained by using a sensitivity analysis are equal to 1.5, 80, and 1000, respectively. Then, the model was evaluated ten times for each TF by setting the algorithm parameters equal to the above values to optimize the operational optimization of case study I. The results of the algorithm implementation with different TFs are presented in Table 4. Figs. 6 and 7 also show the model convergence diagram based on different TFs.

According to Table 4, the best solution for the objective function is related to the based BDA optimization model, developed based on TF6. After 591 generations, the values of the best solution, equal to the average of £ 325,4324 and the standard deviation of 10 times the model run, are equal to £ 327,2350 and 0.0024, respectively.

Moreover, this model ranks fourth compared to other models in terms of convergence and the speed at which it reaches the optimal

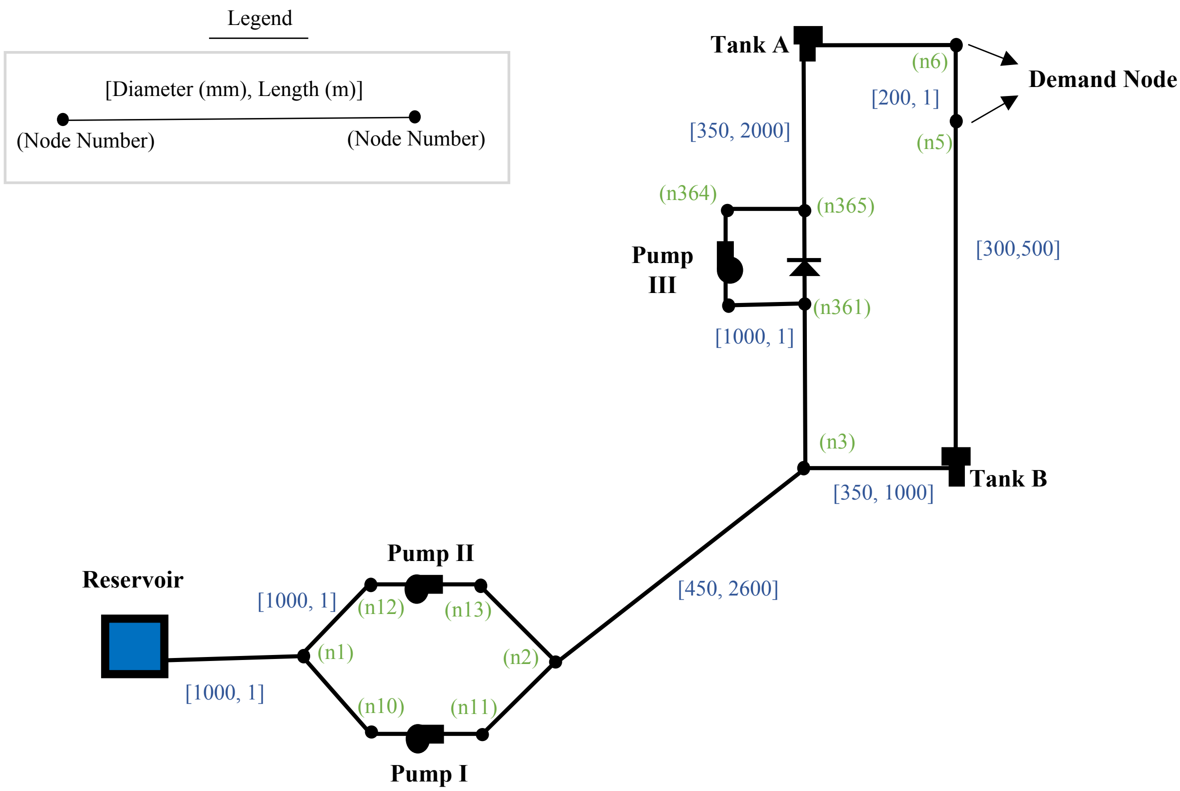

Fig. 4. Schematic of the case study I [16,18].

solution, according to Fig. 7, Figs. 8 and 9 provide the details of the optimal solution, including pump scheduling and reservoir water level in a 24-hour operation period.

For the first time, the case-study network was presented by Van Zyl et al. [16]. Then many researchers carried out their studies on this water network. In the following, the results conducted on this network are compared with others. Various metaheuristic techniques have been applied to the optimization of pump scheduling program on Van Zyl WDS, including evolutionary algorithm (EA) [35], ant colony optimization (ACO) [36], artificial bee colony (ABC), particle swarm optimization (PSO) and fairyfly (FF) [37]. Table 5 compares the obtained results of this study with those of other researchers.

As shown from the result presented in Table 5, the BDA-based model developed in this study outperforms the other models developed previously by different researchers. After evaluating the developed model based on BDA on case study I, it was used to find the optimal schedule for pumping stations in the Shiraz water supply system in southern Iran.

3.2. *Case study II*

In the second case study, the optimal operation of successive pumping stations related to the water conveyance system from Doroudzan dam to Shiraz city is considered (Fig. 10). Droudzan dam is located 120 km from Shiraz city, which provides 61 million cubic meters of water per year for drinking and industrial. Twenty-one million cubic meters of this volume are allocated for a petrochemical facility located 52 Km far from Shiraz. First, the water is transferred to Tank 1 gravitationally from the dam with a fixed volume of 1643 ($\frac{m^3}{s}$). It is then transferred to Tank 2 through pumping station 1. Water in the second station is pumped to the third station and then transferred to the next station placed at a height level. Fig. 11 details the pump performance curve, energy tariff, and demand pattern of the studied water distribution system [38].demand pattern of the studied water distribution system [38].

In most cases, the price of electric energy varies during a 24-h operation period, which is critical in the optimization of energy costs in pumping stations. Therefore, in this case study, energy consumption tariffs during the simulation period are divided into three loads, namely low, medium, and peak load (Fig. 11). It should be noted that the average cost of electrical energy in this study is **£** 0.0065.

3.2.1. *Results and discussion*

The value of the objective function or the cost of energy consumed for the best solution is **£** 994.49 after 587 iterations. Fig. 12 shows the evaluation of the objective function during the optimization procedure and its convergence at the 587 iterations. Also, the pumps' status (on or off) during the operation period is presented in Fig. 13.

Fig. 14 shows the water level changes of the storage tanks in the best solution obtained by the BDA during the operation period. As

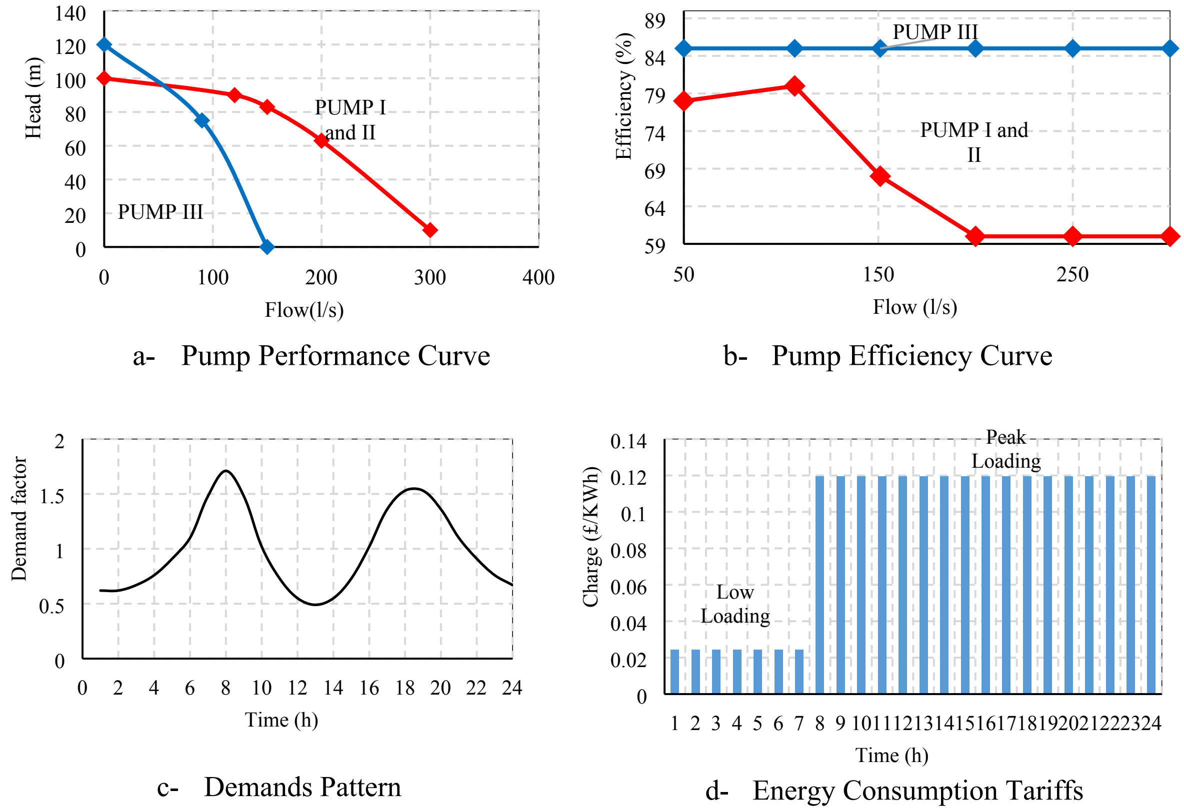

Fig. 5. Operational information of case study I [16].

Table 2
Node Characteristics of case study I [16].

Node Number	Node Name	Elevation (m)	Base Demand (LPS)	Node Number	Node Name	Elevation (m)	Base Demand (LPS)
1	n1	10	0	8	n10	100	0
2	n2	10	0	9	n11	100	0
3	n3	75	0	10	n361	100	0
4	n6	30	100	11	n365	100	0
5	n5	30	50	12	n362	100	0
6	n12	100	0	13	n364	100	0
7	n13	100	0				

Table 3
Tanks Characteristics of case study I [16].

	Bottom elevation	Diameter	Water level		
			Initial	Minimum	Maximum
Tank A	80	20	85	85	95
Tank B	80	25	85	84.5	94.5

can be seen, the minimum and maximum allowable water levels are observed in these reservoirs. Total operating costs and separation of the pumps are presented in Table 6. The maximum and minimum energy consumption are Pump I and Pump VII, with values of 194.59 and 97.86 (£/day), respectively.

Comparing of the total energy consumption cost in the optimal operation mode with the usual operation scenario is also presented in Table 7. As shown in Table 7, the total cost of energy consumed in the optimal scenario is 29.42% less than the average cost of electricity consumed per day compared with the operation. That shows the presented method is successfully optimizes the pumping schedule to minimize the energy cost in pumping stations in water supply systems.

Table 4
The statistics of the objective function achieved by the BDA with different transfer functions.

	BDA-TF1	BDA-TF2	BDA-TF3	BDA-TF4	BDA-TF5	BDA-TF6	BDA-TF7	BDA-TF8
Best	492.309	388.4260	592.1945	413.3551	373.2965	**325.4324**	356.4172	391.8428
Mean	501.1021	395.1546	611.2365	419.010	400.1253	**327.2350**	359.1236	399.1010
Std	0.0183	0.0244	0.0267	0.0041	0.0238	**0.0024**	0.0051	0.0117
Worst	536.3251	401.3251	621.2300	424.4321	411.3205	**330.1031**	361.2130	411.3256

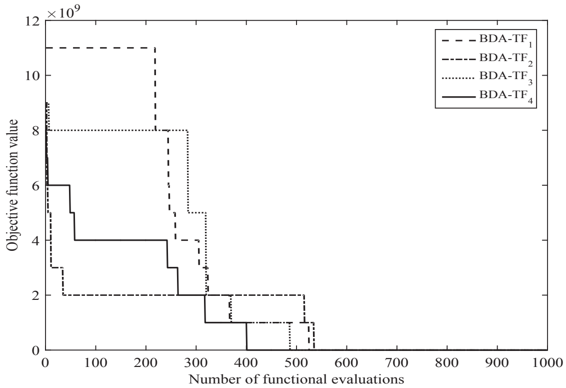

Fig. 6. Convergence curve of the BDA with S-shaped transfer functions in the best run.

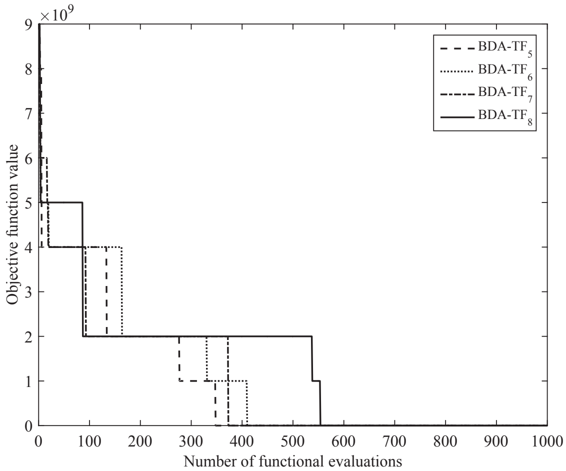

Fig. 7. Convergence curve of the BDA with V-shaped transfer functions in the best run.

4. Conclusion

Optimizing the performance of pumping stations for water distribution systems (WDS) is one of the most important issues that leads to significant savings in energy consumption and financial sources. In this study, the development, application, and analysis of an optimization-simulation model are investigated to optimize the pump scheduling program in 24 h and a one-hour time step. In a pumping schedule, it is determined which pumps will be activated or inactivated at any time while maintaining the physical and operational constraints to the planning goal. For this purpose, the binary dragonfly algorithm with a new transfer function is integrated into the EPANET hydraulic simulation model. The presented model based on the improved dragonfly algorithm was firstly tested in a benchmark network and compared with a previous study using different optimization methods. Without violating the constraints, the proposed model could present the best results of operational costs obtained for the benchmark network. Also, in comparison with the genetic algorithm (GA), GA-hybrid, ant colony optimization (ACO), differential evolution (DE), particle swarm optimization (PSO), artificial bee colony (ABC), and firefly algorithm (FFA), the proposed model has demonstrated a better performance to a minimum value of the objective function. Also, the second case study shows that, while observing all the constraints of the problem, the total cost of energy that is consumed in the optimal operation was reduced up to 29.42%. These results indicate the high performance of the

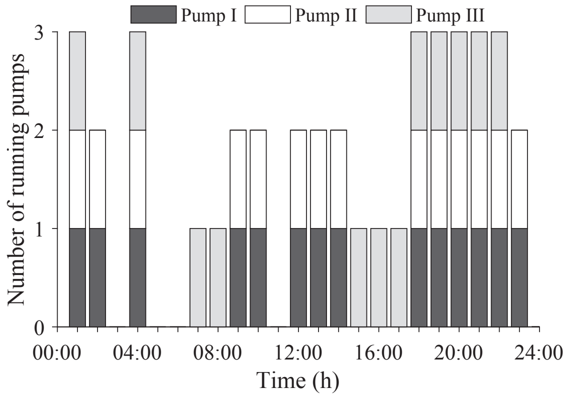

Fig. 8. The pattern of running pumps for the best solution for cade study I.

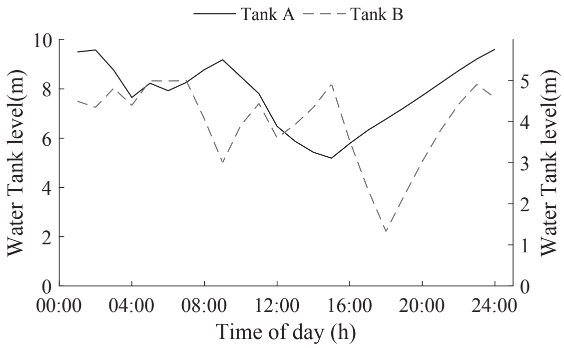

Fig. 9. Variation of the water level in Tank A and B during the 24-h operation period for cade study I.

Table 5
Comparison of optimal obtained answers.

Algorithm	Variables	Authors	Optimal cost (£/day)
GA	Tank level controls (on/off)	Van Zyl et al., [16]	344.19
Hybrid GA			344.43
EA	Tank level controls	López-Ibáñez et al. [35]	337.20
ABC	Tank level controls	Bagirov et al. [37]	363.85
FF			361.72
PSO			363.44
ACO	Pump on/off	Hashemi et al. [36]	388.04
	Pump speed		349.43
BDA	Pump on/off	Proposed approach	**325.23**

developed model to reduce the operating cost of pump stations.

This study developed an improved BDA for optimization pump scheduling problems with a single objective function. Hence, a suggestion for future studies of the multi-objective improved BDA might be the consideration with the other objects such as the maintenance costs of pumps, background leakage of network, reliability, or greenhouse gases.

Declaration of Competing Interest

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

Fig. 10. Schematic of the water conveyance system from the Doroudzan Dam to Shiraz city [38].

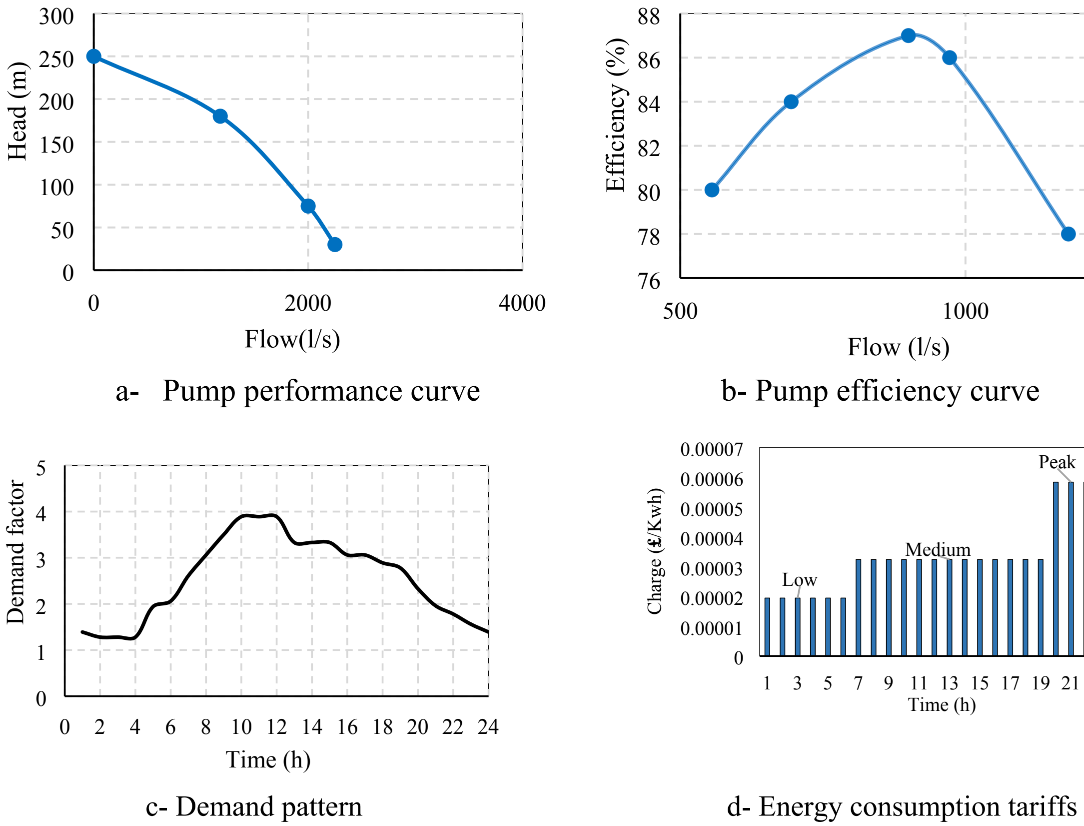

Fig. 11. Operational information of case study II [38].

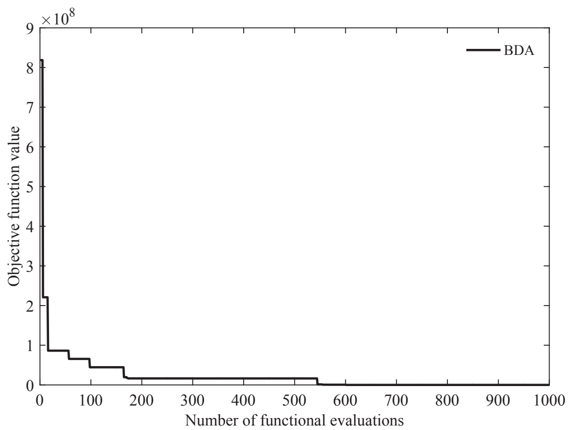

Fig. 12. Schematic of the best solution move toward optimum in the best run.

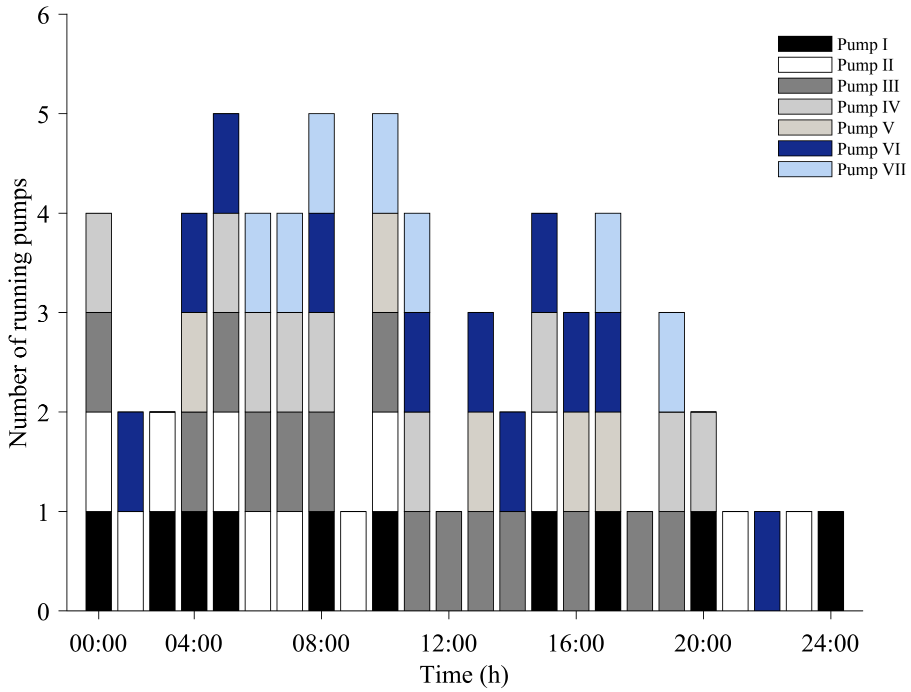

Fig. 13. Pumps scheduling programs for Shiraz water conveyance system from Doroudzan Dam during the 24-hour period.

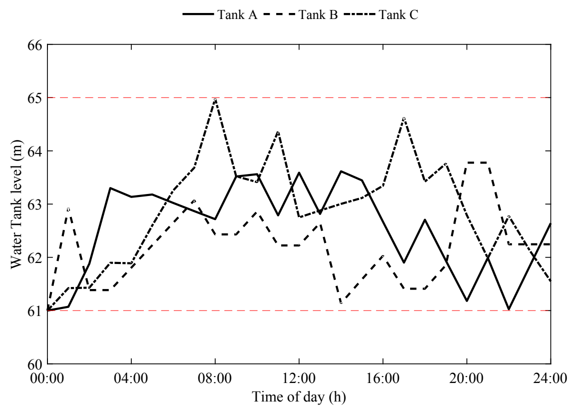

Fig. 14. Water level changes in the reservoir.

Table 6
Total cost of energy during the optimum operationg state.

Pump	Percent Utilization	Average Efficiency	$\frac{Kw-h}{m^3}$	Average Kwatts	Peak Kwatts	Cost (£/day)
Pump I	41.67	82.02	0.60	2320.60	2640.71	133.51
Pump II	45.83	81.66	0.59	2348.96	2643.23	163.91
Pump III	58.33	80.87	0.56	2413.12	2644.67	194.59
Pump IV	37.50	78.00	0.55	2739.11	2743.12	151.09
Pump V	20.83	78.00	0.54	2739.65	2741.79	80.82
Pump VI	45.83	82.78	0.63	2388.43	2546.03	162.13
Pump VII	29.17	83.76	0.63	2321.68	2479.75	97.86
Total Cost						994.49

Table 7
Comparison of the total cost of energy in the optimal operation with non-optimum operation scenario.

Operating Conditions	Cost (£/day)
The average cost of electricity in an average day	1409.07
Cost of electric power in optimum operating conditions(proposed)	994.49

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