EFFICIENT OPTIMIZATION OF PUMP SCHEDULING FOR REDUCTION OF ENERGY COSTS AND GREENHOUSE GAS EMISSIONS

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Abstract - Optimal pump scheduling has been applying to decrease operating costs of water distribution systems (WDSs). However, the operations of pumping stations will result in an increase of Greenhouse gas emission (GHG). To reduce GHG, pumping stations should be operated with high efficiency. For this reason, optimal pump scheduling should take into account both energy cost savings and pumping station efficiency. The aim of this article is to suggest an efficient multi-objective optimization solution for minimizing pumping energy cost and maximizing pumping station efficiency. As a result, a trade-off solution compromising pumping energy cost and pumping system efficiency will be achieved. The Genetic Algorithm (GA) combined with a WDS simulator, EPANET will be applied to solve the pump scheduling problem in one benchmark WDS and the results from our solution will be compared to the ones in the literature in terms of pumping energy cost and efficiency.

Key words - Pump scheduling; Greenhouse gas emissions; pump efficiency; Genetic Algorithm

1. Introduction

Electricity cost of pumping station reaches the most part of the total operating costs of water distribution systems (WDSs). Therefore, minimization of energy costs while delivering water to meet customer demands will be more and more important to water utilities [1-3]. In addition, water demand usually tends to be high in the same diurnal profile as energy demand, which increases the need for pumping during peak energy time periods, thus increasing the need for less efficient electricity generators to enter the market to supply energy. As a result, it will increase greenhouse gas emitting thermal peaking stations driven by coal, diesel, oil or gas [2]. Reducing power consumption of pumping water by raising efficiency would lead to significant reduction in GHG [3-4]. In the USA, average CO_2 emission rate for electricity production is about 0.5 tons per a MWH, hence a 6% decrease in the 100 million MWH would lead to a decrease in Carbonic of 3,000,000 tons. Up to half of this is due to pump operations for water treatment and distribution [2]. Unfortunately, most of pumps are now scheduled aiming to achieve minimization of electrical energy costs exploiting from peak and off-peak electrical tariff time periods [2-5]. This leads to the situation in which water utilities usually operate pumps extensively in low price tariff periods while, in the high price tariff periods, they run pumps rarely without considering efficiency of pumps. Therefore, overall energy consumption is also high and also contributes to the increase of GHG.

The pump scheduling problem was casted as a mixed integer nonlinear program (MINLP) in which binary variables are introduced to represent on/off operations of pumps [3,4]. Many solution approaches concentrating on developing algorithms for solving such the MINLP have been addressed such as dynamic programming (DP), nonlinear programming (NLP), Mixed-integer nonlinear program (MINLP), and heuristic algorithms (i.e, Genetic algorithms, simulated annealing, ...) [5, 7-9].

Dynamic programming (DP) was used early to find the pump scheduling for minimization of the operating cost of small-scale WDSs with a limited number of storage tanks [1]. For large-scaled WDSs, DP was not suitable because a lumped optimization model is difficult to be deduced and computation time is very high. In addition, constraints for ensuring high efficiency of pumping system were not considered in the optimization problem.

For large-scale WDSs, solving the resulting MINLP directly by available MINLP algorithms is not trivial [4]. To deal with this issue, the MINLP solution is found by solving a relaxed nonlinear program (NLP) in the first optimization stage to determine optimal water tank head trajectories, and a mixed-integer solution (i.e., on/off operation of pumps) was found in the second optimization stage so as to track the optimal water tank trajectories [3-5]. However, this solution approach is difficult to accomplish since it is not always possible to find even a feasible MINLP solution providing such optimal tank head trajectories. In addition, the efficiency of pumps is regulated through bound constraints on flow rates of pumps making the formulated MINLP more difficult.

Genetic algorithms (GAs) [6] has been successfully applied to optimize the design and operation of WDSs [7, 8]. Due to no requirement of gradient computation, GAs can be applied to complex, nonlinear, combinatorial optimization problems [9-11]. However, the major disadvantage of GAs lies in its high computational intensity to reach the optimal or near an optimal solution [9, 11]. To overcome the drawback of GAs, many solutions have been addressed. Van Zyl et al. [9] proposed a hybrid optimization scheme combing GAs with local search algorithm like HillClimber to increase GA performance. Broad et al. [11] employed meta-modeling (or a surrogate model) to speed up the simulation task. López-Ibáñez et al. [10] presented a new method representing chromosomes (solutions) for pump scheduling problem where number of pump switches for each pump can be defined in *priori*. The case studies in [9] and [10] are mostly used for studying optimization of water distribution systems. Recently, a prescreened heuristic sampling method based on engineering experience or knowledge was applied to create better initial population of GAs [12]. Improving the operational efficiency of pumping stations has been investigated in [13] using GA. In this approach, valves are placed at outlets of pumps allowing pumps to be operated at high efficiency. It can be concluded that most of the solutions in the literature aimed to improve optimization algorithms so as to achieve reduction of more pumping energy cost while the efficiency of pumping stations was not considered properly.

The pump efficiency is changed after years of usage; therefore employing efficiency data from manufactures to estimate pump efficiency is not reliable [2]. In this article, we propose to use the method of calculating efficiency of a pumping station through electrical consumption power and mechanical power suggested in [13]. This method is suitable for realistic water distribution systems because it is possible to measure electrical power consumption as well as flows and heads of pumping stations. Although this method has been used to improve the efficiency of pumping stations, it has not been applied to optimize operation of a water distribution system with many pipes and tanks considering both pumping system efficiency and operating costs.

Our contribution of this article includes 1) proposing a new multi-objective optimization model for optimal pump scheduling problem; 2) addressing optimal pump scheduling problem for a WDS benchmark. Our results will be compared to others reported in the literature to demonstrate the efficiency of the proposed approach for decreasing Greenhouse Gas emissions.

The article is organized as follows. A new formulation of the multi-objective optimization problem for optimal pump scheduling to simultaneously minimize operating cost and maximize pump efficiency is presented in section 2. Section 3 discusses Genetic Algorithm. A case study is considered in section 4. The conclusion is presented in section 5.

2. A new optimization problem for optimal pump scheduling

2.1. The efficiency of pumping system

We consider a WDS consisting of NPU pumping stations (each pumping station has n_P identical pumps connected in parallel), N_P pipes, N_J junction nodes, and N_T tanks. Operational optimization of WDS is carried out for a time horizon T=24 (hours) with discretization step (k) of 1 hour (k=1, …, 24).

The electrical power consumption at shaft of the pump on link ij at time interval k ($P_{i,j,k}$) can be approximated via the following analytical polynomial [4].

$$P_{i,j,k} = a_0 s_{i,j,k}^3 + a_1 Q_{i,j,k} s_{i,j,k}^2 + a_2 Q_{i,j,k}^2 s_{i,j,k} + a_3 Q_{i,j,k}^3 \quad (1)$$

where coefficients a_0, a_1, a_2, a_3 can be determined from real data of power and flow of pumps (i.e., they are obtained from sensors placed in the WDS). $s_{i,j,k} = n_s/n$ is the relative speed of pump at time interval k with n is the nominal speeds of pumps, and n_s is the operating speed of pumps.

The efficiency of pumping station p ($Eff_{p,k}$) to be maximized at time interval k is calculated by the following equation [13].

$$\text{maximize } Eff_{p,k} = \frac{9810\sum_{i=1}^{n_p} Q_{i,j,k}\Delta H_{j,k}}{1000\sum_{i=1}^{n_p}\left(z_{i,j,k}P_{i,j,k}\right)} \quad (2)$$

where $\sum_{i=1}^{n_p} Q_{i,j,k}$ and $\Delta H_{j,k}$ are the flow and the head increase of pumping station p, respectively; $Q_{i,j,k}$ is the pump flow; $P_{i,j,k}$ is power consumption of the pump calculated by Eq. (1). $z_{i,j,k}$ represents on/off operations of the pump on link ij.

It is noted that equation (2) can be applied for both single speed pumps (SSPs) and variable speed pumps (VSPs). The use of (2) is beneficial because the efficiency equation used in EPANET 2 was proved not to be accurate for calculating the efficiency of variable speed pumps [16].

2.2. Energy cost of pumping systems

The energy cost of pumping stations should be minimized [1, 3]

$$\text{minimize } E = \sum_{k=1}^{T}\sum_{j=1}^{N_{PU}}\sum_{i=1}^{n_P} z_{i,j,k}P_{i,j,k}\gamma_k \quad (3)$$

where γ_k is electrical price tariff at time interval k.

2.3. Constraints

Constraints for the optimal pump scheduling problems consist of equality and inequality ones. The equality constraints are model equations representing hydraulic relations of the WDS while the inequality constraints are to satisfy operation requirements such as sufficient pressure at the demand node, water tank level at the end of the day must be larger than the initial one [4, 5].

2.3.1. Model equations

Energy conservation equations for pipes in link ij [14]

$$H_{i,k} - H_{j,k} - \Delta H_{i,j,k} = 0 \quad (4)$$

where $H_{i,k}$ is the nodal head at node i; $\Delta H_{i,j,k}$ (or $\Delta H_{j,i,k}$) can be computed either by the Hazen-Williams equation

$$\Delta H_{i,j.k} = \frac{10.67L_{i,j}}{D^{4.87}}\left(\frac{Q_{i,j,k}}{C}\right)^{1.852} \quad (5)$$

or by the Darcy-Weisbach equation [3, 14]

$$\Delta H_{i,j,k} = \frac{8L_{ij}f_{ij}}{g\pi^2 D_{ij}^5}\left|Q_{i,j,k}\right|Q_{i,j,k} \quad (6)$$

Energy conservation equations for pumps in link ij [4, 14]

$$H_{j,k} - H_{i,k} - s_{i,j,k}^2\left(A\left(\frac{Q_{i,j,k}}{s_{i,j,k}}\right)^{\alpha} + B\right) = 0 \quad (7)$$

$$ij = 1,\ldots,n_p \times NPU$$

where A, B, and α are coefficients (see Table 1).

Mass balance equations for junction nodes [14]

$$\sum_{j,k} Q_{j,i,k} - \sum_{j,k} Q_{i,j,k} - d_{i,k} = 0;\ i = 1,..,N_J \tag{8}$$

Where $d_{i,k}$ is the demand at node *i*.

Mass balance equations applied for tank node *i* [4, 14]

$$H_{i,k+1} = H_{i,k} + \Delta t \frac{\sum_{j=1} Q_{j,i}}{S_i};\ i = 1,..,N_T \tag{9}$$

where $\Delta t = 3600$; $S_i = \pi \frac{D_i^2}{4}$ is the cross-sectional area of the tank; D_i is the diameter of the tank.

2.3.2. Operational constraints

The flows are bounded by following constraints

$$Q^L \le Q_{i,j,k} \le Q^U \tag{10}$$

In addition, the head constraints should be limited to ensure operational conditions

$$H^L \le H_{i,k} \le H^U \tag{11}$$

The tank level at the end of optimization time period (i.e., *k*=*T*) must be greater than the beginning one (*k*=1). There should be,

$$H_{i,T} \ge H_{i,1} \tag{12}$$

In addition, number of pump switches should be limited

$$\sum_{i=1}^{T-1} \max\left(0, z_{i,k+1} - z_{i,k}\right) \tag{13}$$

2.4. A multi-objective optimization problem

To ensure the trade-off between energy operating costs (i.e., to be minimized) and pumping station efficiency (i.e., to be maximized), we propose the following mixed integer nonlinear program (MINLP) where two objective functions are aggregated into the one. In addition, a penalty function for restricting pump switches is incorporated into the objective function. In this way, the multi-objective function optimization problem is converted into a single objective function optimization problem

$$\text{minimize } w_1 \sum_{k=1}^{T} \sum_{j=1}^{N_{PU}} \sum_{i=1}^{n_P} z_{i,j,k} P_{i,j,k} \gamma_k + w_2 \sum_{p=1} \frac{1}{Eff_{p,k}} + c_{sw} \sum_{i=1}^{T-1} \max\left(0, z_{i,k+1} - z_{i,k}\right)$$

s.t.

$$\sum_{j,k} Q_{j,i,k} - \sum_{j,k} Q_{i,j,k} - d_{i,k} = 0; i = 1,...,N_n$$

$$H_{i,k} - H_{j,k} - \Delta H_{i,j,k} = 0$$

$$\Delta H_{i,j.k} = \frac{10.67 L_{i,j}}{D_{i,j}^{4.87}} \left(\frac{Q_{i,j,k}}{C}\right)^{1.852}; ij = 1,...,N_p$$

$$H_{j,k} - H_{i,k} - s_{i,j,k}^2 \left(A\left(\frac{Q_{i,j,k}}{s_{i,j,k}}\right)^{\alpha} + B \right) = 0$$

$$ij = 1,...,n_p \times NPU$$

$$H_{i,k+1} = H_{i,k} + \Delta t \frac{\sum_{j=1} Q_{j,i}}{S_i}; i = 1,...,NT$$

$$Q^L \le Q_{i,j,k} \le Q^U$$

$$H^L \le H_{i,k} \le H^U$$

$$H_{i,T} \ge H_{i,1}$$

$$z_{i,j,k} = \{0,1\};\ j = 1,...,N_{PU};\ i = 1,...,n_P$$

In these above equations, w_1 and w_2 are weighting coefficients; c_{sw} is penalty coefficient for restricting number of pump switches.

The well-known Genetic algorithm (GA) developed by Holland and Goldberg [6] can solve discrete, non-smooth and non-continuous optimization problems efficiently. For this reason, in this article, we apply GA to solve the MINLP.

3. Genetic algorithm

Genetic algorithm (GA) is an effective stochastic optimization algorithm inspired by the natural selection process which mimics the biological evolution. To find an optimal solution, GA performs the selection, crossover and mutation processes at given probabilities on the current population to produce new children with better survival abilities for the next generation. Over successive generations, all individuals in the population will be converged to the same one which is an optimal solution. In this article, GA is coupled with a hydraulic simulator, EPANET [15] to calculate objective function value and determine constraint satisfaction of the optimization problem (Eq.(4) to Eq.(12)).

3.1. Representation of a chromosome for the pump scheduling problem

A chromosome (i.e., a pump scheduling) consists of a binary string (1,0) representing on/off operations of each pump in each time interval and a real string with values ranging from 0.0 to 1.0 describing relative speeds of pumps. As a result, the length of a binary string will be *NPU*×*T*×n_p and the length of a real string will be *NPU*×*T*. To the end, a chromosome (solution candidate) for pump scheduling problem, in general, are shown in Figure 1.

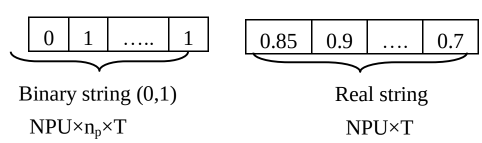

Figure 1. *A chromosome for the pump scheduling problem*

3.2. Constraint handling methodology

EPANET [15] is mostly common to be used for simulating the WDS. As a result, the equality constraints of the MINLP will be handled by means of simulation. Constraint violations are mostly due to violations of bound constraints in (10)-(12), simulation errors ($Epanet\_Err$) and/or simulation warnings ($Epanet\_Warn$) resulted by EPANET. In order to obtain feasible solutions, these violations must be handled via penalty function or via a methodology of dominant individuals in [17]. In this article, we propose to apply both of the handling constraint approaches. We suggest the following objective function

$$\text{minimize} \quad w_1 \sum_{k=1}^{T} \sum_{j=1}^{N_{PU}} \sum_{i=1}^{n_P} z_{i,j,k} P_{i,j,k} \gamma_k$$
$$+ w_2 \sum_{p=1} \frac{1}{Eff_{p,k}} + c_{sw} \sum_{i=1}^{T-1} \max\left(0, z_{i,k+1} - z_{i,k}\right)$$
$$+ c \times \sum_{i} \max\left(0, H_{i,1} - H_{i,T}\right)$$

The violations of constraints corresponding to bound constraints are measured by.

$$Cstr_i = \max\left(0, H_{i,k} - H^U\right) + \max\left(0, H^L - H_{i,k}\right)$$
$$Cstr_{ij} = \max\left(0, Q_{i,j,k} - Q^U\right) + \max\left(0, Q^L - Q_{i,j,k}\right)$$

The total constraint violation level is

$$Cstr = Cstr_{ij} + Cstr_i + Epanet\_Err + Epanet\_Warn$$

According to the constraint handling methodology in [17], GA will select individuals with lower violations of constraints ($Cstr$). And, if two individuals have the same violations of constraints, GA will select the ones with lower objective function values. With this fashion, individuals with feasible solutions will be selected in priority. The tank constraint (12) is satisfied and the number of pump switches is limited by penalty functions incorporated in the objective function. GA is carried out with a population of 100 individuals, crossover probability p_c= 0.9, and mutation probability p_m=0.1. Maximum number of iterations is 1000. $c = 100$; $c_{sw} = 10$; $w_1 = 0.7$; $w_2 = 0.3$.

4. Case study

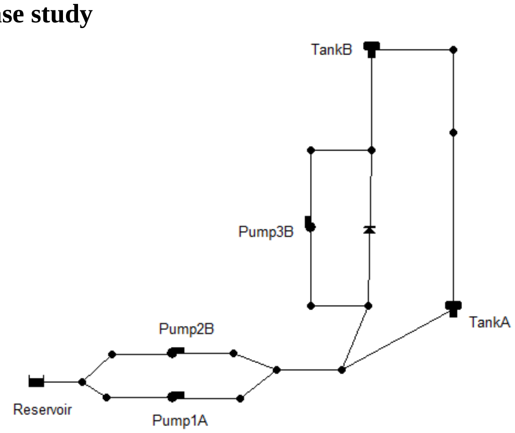

Figure 2. *VanZyl water distribution network [9]*

The van Zyl WDS benchmark in [9] will be used for minimization of operating cost and maximization of pumping station efficiency as depicted in Figure 2. The WDS consists of three pumps, two tanks, and one reservoir. Two scenarios are considered. The first one is that all pumps are single speed pumps (i.e., pumps run at their rated speeds) and the second one is that all pumps are variable speed pumps, i.e., pump speeds can be adjusted through variable frequency drivers (VFDs)

From the data of pumps in [9], power consumption characteristics of pumps 1A, 2B, and 3B can be approximated by second polynomials as in Table 1 respectively.

Table 1. *Characteristics of pumps*

Pump	Power consumption characteristics (kW)
Pump 1A, 2B	P = -5736Q^3 + 671.4Q^2 + 1165.3Q + 0.6192
Pump 3B	P = -56044Q^3 - 965.68Q^2 + 1406.3Q - 0.0063

4.1. Scenarios 1: Optimal operation scheduling of single speed pumps

Since GA is a stochastic algorithm, we run it ten times to choose the best pump scheduling [i.e., in [9], [10] GA is carried out 5 times]; the result is shown in Table 2.

Table 2. *Optimal on/off operations of pumps*

Time [hours]	**Pump sates (on/off)**			**Time**	**Pump sates (on/off)**		
	Pump 1A	Pump 2B	Pump 3B		Pump 1A	Pump 2B	Pump 3B
1	1	1	0	13	0	0	1
2	1	1	0	14	0	0	1
3	1	0	1	15	0	0	1
4	1	0	1	16	1	0	1
5	1	0	0	17	1	0	1
6	1	0	0	18	1	1	1
7	1	0	0	19	1	1	1
8	1	0	0	20	1	1	1
9	0	0	0	21	1	1	1
10	0	0	0	22	1	1	1
11	0	1	0	23	1	1	1
12	0	0	0	24	1	1	1

With the optimal pump scheduling, the efficiencies of pumps are shown in Figure 3. It can be seen that, in most of operation time, pump 1A and 2B are operated at high efficiencies ranging from 66% to 77%.

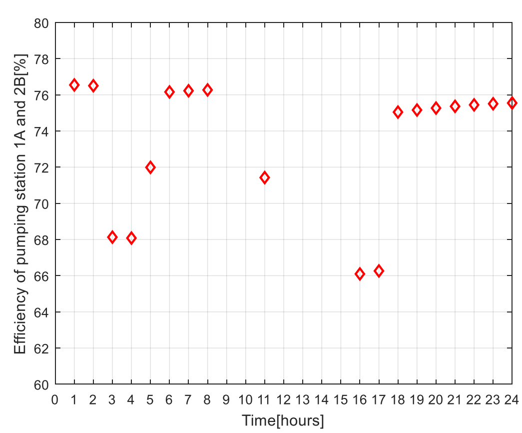

Figure 3. *Efficiency of pumping station (1A and 2B)*

In addition, the trajectories of water heads in Tank A and Tank B for 24 hours given in Figure 4 reveal that the pumping energy cost is saved.

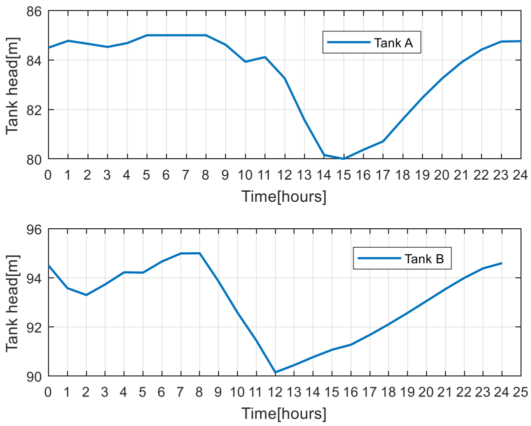

Figure 4. *Profiles of water head of tank A and B*

In particular, Tank A and Tank B are filled with water in off-peak electrical tariff time periods (from time intervals 18 to 24) and they are drained to supply water for the WDS during peak electrical tariff time periods (from time interval 1 to 17). As seen in Table 2, all pumps are scheduled to operate during the off-peak time periods. This is the reason the energy cost is saved. The resulting of energy cost and number of pump switches are given in Table 3 together with those reported in [9] and [10]. It can be seen that the solution found by using our approach leads to an energy cost of 327.5 ($) with a total of 5 pump switches.

Table 3. *Comparisons of solution approaches*

	Our solution approach	López-Ibáñez et al. [10]	VanZyl et al. [9]
Energy costs ($)	327.5	326.5	344.0
Number of pump switches	5	9	5

In comparison with the solution reported in [9], our solution leads to a bit higher energy cost (i.e, 1$), but with a less number of pump switches. Compared to the solution reported in [10], our solution is better in both energy cost and number of pump switches.

4.2. Scenarios 2: Optimal operation scheduling of variable speed pumps

Now we consider the case where all pumps are variable speed pumps. In practice, variable frequency drivers (VFDs) are commonly used to regulate pump speeds. Similar to the first scenarios, after running GA ten times, we obtain the best optimal pump speeds for each pump as given in Table 1. With such pump scheduling, the resulting energy cost is 301$.

Table 4. *Optimal pump speeds*

Time [hours]	Relative pump speed			Time	Relative pump speed		
	Pump 1A	Pump 2B	Pump 3B		Pump 1A	Pump 2B	Pump 3B
1	0.89	0.89	0.80	13	0.84	0.84	1.00
2	0.83	0.83	1.00	14	0.90	0.90	1.00
3	0.00	0.00	0.45	15	0.88	0.88	0.97
4	0.00	0.00	0.40	16	0.77	0.77	1.00
5	0.00	0.00	0.90	17	0.86	0.86	0.92
6	0.00	0.84	0.30	18	0.98	0.98	0.94
7	0.84	0.84	0.70	19	0.97	0.97	0.85
8	0.83	0.83	0.71	20	0.99	0.99	0.97
9	0.89	0.89	0.35	21	0.98	0.98	0.97
10	0.78	0.78	0.87	22	1.00	1.00	0.97
11	0.89	0.89	0.79	23	1.00	1.00	0.96
12	0.84	0.84	0.82	24	1.00	1.00	0.91

It can be seen that, using VFDs for regulating pump speeds, we can achieve more energy cost savings. Indeed, we further save 26($) of the energy cost as compared with the energy cost in the first scenarios. More importantly, the efficiencies of pumps are significantly improved. As seen in Figure 5, the efficiencies of pumping stations are at least 75%. Especially, during peak tariff time periods (from time intervals 1 to 17), pumps are operated at high efficiencies. The increase of pump efficiency will result in less electrical power consumption, and hence many inefficient generators can be avoided and GHG is reduced.

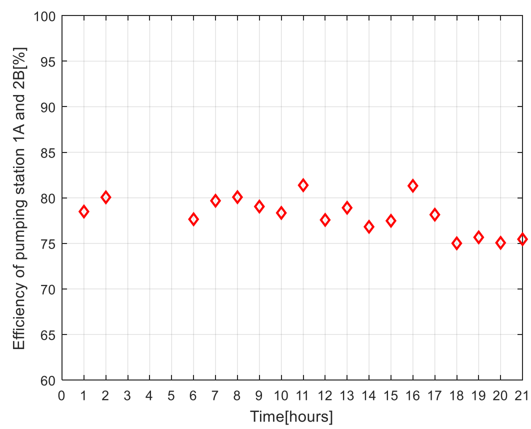

Figure 5. *Efficiency of pumping station (1A and 2B)*

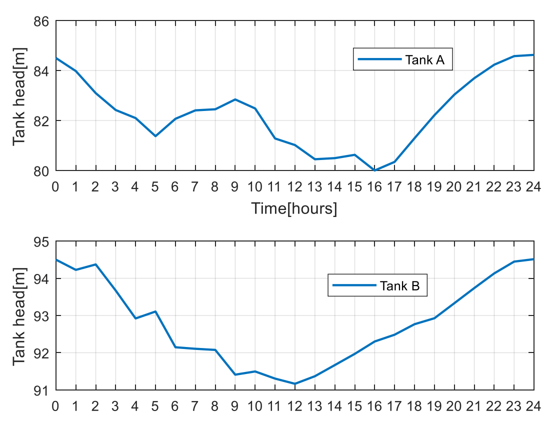

Figure 6. *Profiles of water head of tank A and B*

Optimal water tank heads given in Figure 6 demonstrate that from time intervals 17 to 24, most of pumps are operated to pump water to the tanks, and water in the tanks will be drained to supply water for the WDS during peak- time periods.

In both case studies, pump switching is restricted by a penalty function. Starting pumps certainly consumes a lot of electric power and this issue will be considered in future studies. The simulation of the WDS was carried out by EPANET [15] may be enhanced by using a parallel computation technique, which will be also our future study.

5. Conclusion

In this article, we have proposed a new and efficient multi-objective optimization problem for minimization of pumping energy cost and maximization of pumping station efficiency. By slightly increasing operational efficiency of pumps, we can further reduce electrical power consumption of pumps and thus decrease GHG. The newly proposed optimization model will not only help water utilities to achieve energy cost savings, but also contribute to the reduction of GHG. Moreover, the results in this article imply that using VFDs for regulating pump speeds will certainly attain both high efficiency of pumps and energy cost savings.

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