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# Fast Pump Scheduling Method for Optimum Energy Cost and Water Quality in Water Distribution Networks with Fixed and Variable Speed Pumps

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## ***Abstract***

Supplying high quality water at competitive cost is a major challenge for water utilities worldwide, especially with ever increasing water quality standards and energy prices. A number of pump scheduling methods for optimising simultaneously water quality and energy cost have been developed already. However, none of these methods is ideal due to the complexity of water networks and the nonlinear behaviour of water flow. In this research, a new optimisation method named iterative Extended Lexicographic Goal Programming (iELGP) is developed to optimize energy cost and water quality (residual chlorine) in water networks with a mixture of fixed speed pumps (FSPs) and variable speed pumps (VSPs). Two different approaches were used to indirectly improve chlorine. The new method was tested on the C-Town water network and compared with the graph theory method of Price and Ostfeld (2016). The results obtained show the ability of the iELGP method to optimize energy cost and water quality in water networks and in a computationally very efficient manner. They also show that the iELGP method can identify lower energy cost pump schedules and do this faster than the above comparison method. Using VSPs instead of FSPs improves the water quality and decreases the related energy and maintenance cost in water networks.

***Keywords***

Pump scheduling, Goal Programming, Energy Cost, Water Quality, Variable Speed Pumps.

## Introduction

A recent comprehensive literature review of more than 200 publications on pump scheduling (Mala-Jetmarova et al 2017) has concluded that "water distribution operational optimisation problems are far from being solved, despite the large body of literature on this subject published over the last 20-30 years." This is because the truly holistic pump scheduling problem formulation that addresses all relevant issues related to water flow, quality, operational risks and costs of energy and power used is currently misisng. Additonaly, there is still no agreement on the unique best optimisation method that gives global optimum solution in a short computational time for a general water distribution network.

Simulatonuous optimisation of energy cost and water quality in water networks is important to ensure that energy cost is minimized without worsening the water quality. Several attempts to achieve this have been made in the past. Mehrez et al. (1992), Ostfeld and Shamir (1993a), Ostfeld and Shamir (1993b) and Percia et al. (1997) all used Non-Linear Programming (NLP) to minimize energy cost with water quality substances at demand nodes being constrained (or penalized in the objective function). However, all these approaches were made for conservative water quality substances that do not decay, hence these approaches cannot be used for optimization of chlorine concentration in water networks.

Goldman and Mays (1999) and Sakarya and Mays (1999) linked the hydrualic and water quality simulator EPANET with Simulated Annealing (SA) and NLP optimisation methods; respectively, to minimize pumping energy cost whilst constraining chlorine concentrations at demand nodes. Both methods were applied on the same case studies and their results were compared. Both methods needed to be run multiple times with different values for optimisation parameters to ensure optimality of the solution.

Biscos et al. (2002) and Biscos et al. (2003) used Mixed Integer Non-Linear Programming (MINLP) to minimize energy cost and to maintain the required chlorine concentration at demand nodes. However, the method required the network model to be simplified and could result in practically infeasible solutions.

Genetic Algorithms (GA) was used in multiple approaches to optimize energy cost and chlorine in water networks (Ostfeld and Salomons 2006; Gibbs et al. 2010a). Murphy et al. (2007) used GA to minimize energy cost and water age, which is inversely proportional to chlorine in water network. However, GA, used in all these approaches, is a computationally expensive optimisation method. Artificial Neural Networks (ANN) were used to address this issue (see e.g. Broad et al. 2010) but the downside of this is that ANN needs to be trained prior to optimisation which requires substantial computational time as well. Also, the ANN based approach may still give inaccurate or suboptimal solutions due to ANN’s inability to act as a perfect surrogate model.

Kurek and Ostfeld (2014) used the Strength Pareto Evolutionary Algorithm II (SPEA2) multi-objective optimisation method to optimize cholorine, water age, tank sizing cost, and pumping energy cost in water distirbution networks that have VSPs. Authors claim that generating a Pareto set with pump relevant schedules for 24 hours took approximatly 4 hours for EPANET Example 3 network (USEPA, 2013). Thus, the method cannot be used for real-time control.

The use of VSPs instead of FSPs reduces the energy consumption, reduces the leakage, reduces the number of pump switches, and provides a better control in water distribution networks (Wood and Reddy 1995; Lamaddalena and Khila 2012). Despite of these potential benefits of VSPs, many existing pump scheduling methods including some recent ones (Giacomello et al. 2013; Odan et al. 2015) did not consider the VSPs, most likely because this increases the complexity of the pump scheduling problem. Having said this, a number of papers did consider scheduling the operation of VSPs.

Several attempts to schedule the operation of VSPs relays on problem decomposition which could result in suboptimal solution. Coulbeck et al. (1988a) and Coulbeck et al. (1988b) solved the problem by decomposing it into three levels. The upper level finds optimum tanks' trajectories, then the intermediate level finds optimum flow from each pumping station, and finally the lower level finds the optimum operation of pumps in each pumping station. Ulanicki et al. (2007) solved the problem in two levels. The first level treats the number of pumps switched on during a time step as continuous decision variable (i.e. allowing fraction of pump to start during a time step), then in the second level, Branch and Bound method is used to find optimum integer number of running pumps and their speeds during each time step. Pump scheduling method should directly solve for the speed of each pump during each time step to ensure optimality of the solution.

Some of the previous attempts to optimise VSPs depended on discretisation of the VSP speed (Chen and Coulbeck 1991, Ulanicki et al. 1993; Pezeshk and Helweg 1996, Moreira and Ramos 2013). However, discretisation increases number of decision variables, computation time, and leads to suboptimal solution.

Several existing pump scheduling methods used metaheuristic methods like GA (Lingireddy and Wood 1998; Kelner and Leonard 2003; Wu 2007; Wu and Zhu 2009; Selek et al. 2012), Particle Swarm (Wegley et al. 2000), Ant Colony (Hashemi et al. 2013) to optimize the operation of VSPs. In Rao and Salomons (2007), ANN are used in conjunction with GA to reduce the computational time for hydraulic calculations. As mentioned previously, metaheuristics and ANN are time expensive and might give suboptimal solutions.

Verleye and Aghezzaf (2015) used Generalized Bender Decomposition Algorithm to schedule the operation of VSPs. The method gives optimal solution for large water networks, however the authors claim that the method needs to be carefully constructed and it includes parameters that need to be tunned, otherwise the method will be computationally intensive and give suboptimal solutions. Thus, the method is not fully automated and requires preparatory work prior optimisation.

Several existing pump scheduling methods assumed constant efficeincy of VSPs, regardless of the speed, for the sake of simplicity (Chen and Coulbeck 1991; Kurek and Ostfeld 2013). However, efficiency of VSP changes with speed and flow (Morton 1975; Sárbu and Borza 1998). If true efficiency is not used, then the calculated power for a VSP running at low speed will be lower than the actual power used resulting in inaccurate energy cost estimate and hence suboptimal solution identified.

The initial development of the new iELGP pump scheduling methodology presented in this paper is available in Abdallah and Kapelan (2017). The main objective of the initial development was to minimize the energy cost of FSPs in a computationally efficient manner, for water distribution networks with multiple tanks and pumping stations. In this research, the iELGP pump scheduling method is further extended to optimize the operation of VSPs, to improve the water quality (chlorine) in water networks and to overcome multiple deficiencies of exiting scheduling approaches (mentioned in above paragraphs). Indeed, unlike in most existing pump scheduling approaches, the new iELGP pump scheduling methodology proposed here can schedule simulateneously both fixed and variable speed pumps (with both being modelled using true pump efficiency) whilst addressing energy cost and water quality issues in a general water distirbution system. The methodology is based on a computationally fast iELGP optimisation method which makes use of linearised energy cost and other equations and continuous decision variables to present pump schedules and speeds. This method also does not have parameters to calibrate hence overcoming the related difficulties with GA and many other heuristic optimisation methods developed over the years. Despite this, as it will be illustrated in the case study, the new methodology is capable of identifying near optimal solutions.

This paper is organized as follows. First, the problem and the assumptions used to solve the problem are mentioned. Then, the paper presents in detail iELGP method and the solution steps for the problem. Then, the method is applied on a water network that was used to test another pump scheduling method, and the results obtained from iELGP method and the other method are compared and discussed intensively. Finally, the key findings are summerized and the future recommendations are mentioned.

## Methodology

### *Pump Scheduling Problem and Assumptions*

The pump scheduling problem is formulated and solved here as an optimisation problem driven by the minimization of pumping energy cost whilst indirectly improving the residual chlorine in the network (details below). This problem is subjected to a number of constraints shown below.

Pump scheduling problem is an NP-hard problem due to its non-linearity and non-convexity (D'Ambrosio et al. 2015, Verleye and Aghezzaf 2015). The non-linearity is due to the non-linear relationship of pump's head with respect to flow, the non-linear relation between head loss and flow in pipes and the non-linear water quality changes in the system, due to nonlinearity of reactions and water mixing inside pipes and tanks. The non-convexity in pump scheduling problem comes from the changing flow paths in pipes and tanks, different discrete choices of pumps to run at a given time of the day and the nonlinearity of the scheduling problem which is present in both optimisation objectives and constraints. In addition to above, water quality simulation typically requires a short time step (e.g. 5 minutes) and long time horizons, to reach periodic behaviour.

All of the above makes the pump scheduling problem addressed here computationally expensive, especially for larger real life networks. Given this, the pump scheduling problem is relaxed here using the following assumptions:

1. The optimisation period is divided into time steps of fixed length. During each time step, demand is assumed to be known and fixed. Pumps' operating points during each time step are also fixed and will be determined by the optimisation method. These assumptions were used in the initial development of iELGP method in Abdallah and Kapelan (2017) and in most pump scheduling methods available in literature.
2. VSPs are allowed to run at specific relative speeds (defined as fractions of the maximum speed) ranging between 0.7 and 1.0. This is done for the following reasons: (a) VSP relative

efficiency (efficiency at actual speed over efficiency at maximum speed) is high i.e. almost equal to 1 in this range (Marchi et al. 2012; Coelho and Andrade-Campos 2016); (b) the efficiency of Variable Frequency Drive (VFD), the most common technology used to vary the speed of pump's motor, is usually between 95% and 98% in the aforementioned range of relative speeds and it drops significantly at lower speed (Ulanicki, et al. 2008). Additionally, motor's efficiency increases with the increase in its load and most motors reach their maximum efficiency when their load is above 75% of their rated load (Kaya et al. 2008; Marchi and Simpson 2013; Kalaiselvan et al. 2016). Please note that there are other energy losses that varies with speed such as pump-motor vibrations (Luo et al., 2012), efficiency of pump-motor coupling (e.g. magnetic coupling, oil coupling), efficiency of electric cables (Moreno et al., 2007). However, these energy losses have not been included in the work presented here.

Note that constraining the relative speed of VSPs between 0.7 and 1.0 requires VSPs not to be oversized, otherwise running oversized VSPs at high speeds will increase discharge pressure, leakage and energy consumption.

3. The minimum required chlorine at demand nodes can be achieved implicitly by decreasing tanks' maximum water level (Kennedy, et al. 1993; Oslon and Deboer 2011; Price and Ostfeld 2016). This prevents storing big amounts of water for long time and keeps water fresh. However, doing so might decrease the pressure at demand nodes. Additionally, it is not a good choice for emergency or maintenance cases when tanks are needed to recover water shortage in the network. Given this, alternative approach is used here (to have the minimum required chlorine at demand nodes) which is to keep tank's storage capacity as it is and to minimize the inlet/outlet flow. This, in turn, enables providing sufficient water in tanks for emergency cases and, at the same time, chlorine concentration in the network is improved.

   Note that tank's inlet/outlet flow is minimized to a rate that doesn't worsen the chlorine level in the tanks themselves. Note also that both approaches do not take chlorine at demand nodes into account during the optimisation. Instead, chlorine at demand nodes is evaluated using the water quality simulator in the post processing phase of the optimisation.

> The above two approaches are used here to shed the light on pump scheduling as an important tool not only to reduce energy cost but also to improve water quality without the need to add chlorine boosters or increase chlorine dosing set-points. These approaches might be of interest for water utilities, and could draw their attention to the decay in water quality caused by excessive use of tanks. Additionally, our approach allows to improve water quality in a fast manner without dealing with the nonlinear water quality equations.

The aforementioned two-objective pump scheduling is solved here by using iELGP method, a variant of goal programming (GP) method that was introduced by Romero (2001). The iELGP is a promising new method that has already shown great potential for solving a more conventional pump scheduling focused on energy minimisation only (Abdallah and Kapelan 2017).

In iELGP, each goal (i.e. objective) must be a linear function of decision variables. In addition, each objective is given a target and the deviation between the value of the objective and its target is then minimized. Therefore, the aforementioned two objectives are combined into the following single objective function:

$$Minimize\ PEC_i + w.\sum_{z=1}^{Z}\sum_{t=1}^{T}(PVC_{z,t,i} + NVC_{z,t,i}) \qquad \forall i \in I \qquad \text{Eq. (1)}$$

where $PEC_i$ = positive deviation variable for energy cost at iteration *i* (£); $PVC_{z,t,i}$ = positive deviation variable for water volume change in tank *z* ($m^3$); $NVC_{z,t,i}$ = negative deviation variable for water volume change in tank *z* ($m^3$); $w$ = weighting factor; $i$= iELGP iteration index; $I$= total number of iterations; *z* = tank index; $Z$ = total number of tanks; $t$ = time step index; and $T$ = total number of time steps. Note that in each time step one of the deviation variables $PVC_{z,t,i}$ and $NVC_{z,t,i}$ is equal to or greater than zero and the other one is equal to zero due to the nature of GP.

The positive deviation variable for energy cost is defined as follows:

$$PEC_i = EC_i - ECT \qquad \forall i \in I \qquad \text{Eq. (2)}$$

where $EC_i$ = energy cost at iteration $i$ (£); and $ECT$ = energy cost target (£). The energy cost target $ECT$ is an ideal, optimistic value that cannot be reached in real life. Thus, the achieved energy cost $EC_i$ will always positively deviate from the energy cost target $ECT$ by an amount equal to $PEC_i$. $ECT$ is estimated initially as described in the next section.

Further, energy cost for pumps (VSPs and FSPs) is calculated as follows:

$$EC_i = \sum_{t=1}^{T}\left(\left(\sum_{v=1}^{V} P_{v,t,i}^{\substack{Actual \\ Speed}} + \sum_{f=1}^{F} P_{f,t,i} \,.\, x_{f,t,i}\right) .\, E_t \,.\, S_t\right) \qquad \forall i \in I \qquad \text{Eq. (3)}$$

Where $P_{v,t,i}^{\substack{Actual \\ Speed}}$ = VSP power at actual speed; $v$ = VSP index; $V$ = total number of VSPs; $P_{f,t,i}$ = FSP power; $x_{f,t,i}$ = decision variable denoting pump $f$ status; $f$ = FSP index; $F$ = total number of FSPs; $E_t$ = cost of electricity for given time step $t$ (£/KWh); and $S_t$ = time step length (hr).

Affinity Laws provide a good approximation for VSPs power when they are run at high speeds (Simpson and Marchi 2013). The relative power curve is almost linear for relative speeds between 0.7 and 1.0 (Coelho and Andrade-Campos 2016) hence it is possible to fit the following regression line:

$$P_{v,t,i}^{\substack{Actual \\ Speed}} = \left(s \,.\, x_{v,t,i} - y \,.\, b_{v,t,i}\right) . P_{v,t,i}^{\substack{Maximum \\ Speed}} \qquad \forall v \in V, \forall t \in T, \forall i \in I \qquad \text{Eq. (4)}$$

where $P_{v,t,i}^{Maximum\ Speed}$ = VSP power at maximum speed; $s$ = the slope of the regression line which is equal to 2.1850; $x_{v,t,i}$ = decision variable denoting relative speed of VSP $v$ at time $t$ and iteration $i$; $y$ = the y-intercept of the regression line which is equal to 1.2176; and $b_{v,t,i}$ = binary variable that is equal to zero when pump is not running and equal to one when pump is running. The fitted regression line in Eq. (4) has coefficient of determination equals to 0.9899. Note that whilst the values of $s$ and $y$ are virtually constant for a VSP running at relative speed between 0.7 and 1.0, the same cannot be claimed for the relative speeds below 0.7.

The relative VSP speed is constrained as follows:

$$x_{v,t,i} = \begin{cases} 0, & \text{If pump is not running} \\ 0.7 \le x_{v,t,i} \le 1.0, & \text{If pump is running} \end{cases} \quad \forall v \in V,\ \forall t \in T,\ \forall i \in I \qquad \text{Eq. (5)}$$

The minimum speed can be increased to more than 0.7 in case the pump is under-sized, to avoid getting zero flow.

Branch and bound method (Land and Doig 1960) is used to find the optimum value of $x_{v,t,i}$ during optimisation.

Pump power $P_{v,t,i}^{\substack{Actual\\Speed}}$ in Eq. (4) should be equal to 0 when pump speed $x_{v,t,i}$ is equal to 0. Thus, the second term in Eq. (4) is multiplied by binary variable $b_{v,t,i}$. The following two constraints are applied with the aim to enforce $b_{v,t,i}$ to be equal to 1 when $x_{v,t,i}$ is between 0.7 and 1.0 and to enforce $b_{v,t,i}$ to be equal to 0 when $x_{v,t,i}$ is equal to 0:

$$b_{v,t,i} \ \ge \ x_{v,t,i} \qquad \forall v \in V, \quad \forall t \in T, \quad \forall i \in I \qquad \text{Eq. (6)}$$

$$s \,.\, x_{v,t,i} - y \,.\, b_{v,t,i} \ge 0 \qquad \forall v \in V, \quad \forall t \in T, \quad \forall i \in I \qquad \text{Eq. (7)}$$

The VSP power at maximum speed can be calculated using the following equation:

$$P_{v,t,i}^{Maximum\ Speed} = \frac{\gamma Q_{v,t,i}^{Maximum\ Speed}\ h_{v,t,i}^{Maximum\ Speed}}{\eta_{v,t,i}^{Maximum\ Speed}} \qquad \forall v \in V, \forall t \in T, \forall i \in I \qquad \text{Eq. (8)}$$

where $\gamma$ = specific weight of water (kN/m$^3$); $Q_{v,t,i}^{Maximum\ Speed}$ = flow rate (m$^3$/h) of pump *v* running at maximum speed; $h_{v,t,i}^{Maximum\ Speed}$ = head (m) of pump *v* running at maximum speed; and $\eta_{v,t,i}^{Maximum\ Speed}$ = efficiency of pump *v* running at maximum speed. The values of $Q_{v,t,i}^{Maximum\ Speed}$ , $h_{v,t,i}^{Maximum\ Speed}$ and $\eta_{v,t,i}^{Maximum\ Speed}$ will be adjusted after each iteration upon the feedback from the hydraulic simulator as will be shown is the next section.

For FSPs, the decision variable $x_{f,t,i}$ in Eq. (3) is the fraction of time step during which the pump is running and it is constrained:

$$0 \leq x_{f,t,i} \leq 1 \qquad \forall f \in F, \quad \forall t \in T, \quad \forall i \in I \qquad \text{Eq. (9)}$$

If $x_{f,t,i}$ is equal to zero, then the pump is off and if $x_{f,t,i}$ is equal to one, then the pump is on for the full duration of time step *t*. However, if $x_{f,t,i}$ has a value between zero and one then pump is on from the beginning of time step $t$ for duration equal to $x_{f,t,i}S_t$ and then it is off until the end of that time step. Other options like FSP is off in the first part of the time step and then turns on within the same time step are not considered in our methodology. This is because having the other options would increase the computational time (due to increase in trials and iterations) without having significant beneficial effect on the optimality of the solution, especially if the time step length is not long (e.g. 1 hour) which is usually the case.

The following equation is used to calculate the FSP power:

$$P_{f,t,i} = \frac{\gamma Q_{f,t,i}\, h_{f,t,i}}{\eta_{f,t,i}} \qquad \forall f \in F, \quad \forall t \in T, \quad \forall i \in I \qquad \text{Eq. (10)}$$

where $Q_{f,t,i}$ = flow rate (m$^3$/h) of pump *f*; $h_{f,t,i}$ = head (m) of pump *f*; and $\eta_{f,t,i}$ = efficiency of pump *f*. The values of $Q_{f,t,i}$, $h_{f,t,i}$, and $\eta_{f,t,i}$ will be adjusted after each iteration upon the feedback from the hydraulic simulator as will be shown is the next section.

If a group of parallel FSPs exists in a water network and they are all identical then what matters only is the number of pumps running in each time step (Gleixner, et al. 2012; Menke, et al. 2016; Bonvin, et al. 2017). Thus, the following constraint is used for each group of identical parallel FSPs:

$$x_{g,t,i} \geq x_{g+1,t,i} \geq \cdots \geq x_{G,t,i} \qquad \forall t \in T, \quad \forall i \in I \qquad \text{Eq. (11)}$$

where $g$ = is pump index in a group of parallel FSPs; and $G$ = total number of pumps in a group of parallel FSPs. If all parallel FSPs in a group are identical then the number of possible solutions reduces from $2^G$ to $G + 1$ in each time step; thus reducing computational time.

Further, parallel identical VSPs should run at the same relative speed to have the same outlet flow rate from each pump. This concept is known as load sharing (Jones, et al. 2008) and it reduces the energy consumption, number of possible solutions and computational time. To enable load sharing concept in the iELGP method, parallel identical VSPs are remodelled into combined pumps. Each combined pump has head, efficiency, and power curves of certain number of pumps in parallel. For example, if there is a group of two identical parallel VSPs, then these pumps should be remodelled into the following two combined pumps: (1) the first combined pump has head, efficiency, and power curves of one pump and (2) the second combined pump has head, efficiency, and power curves of two pumps in parallel. Only one combined pump is allowed to start during each time step. Thus, the following constraint is used for each group of parallel identical VSPs:

$$\sum_{cv=1}^{CV} b_{cv,t,i} \leq 1 \qquad \forall t \in T, \quad \forall i \in I \qquad \text{Eq. (12)}$$

where $cv$ = index of combined VSP; and $CV$ = total number of possible VSPs combinations in a group of parallel identical VSPs.

The negative and positive deviation variables for water change in each tank during each time step can be calculated as follows:

$$NVC_{z,t,i} - PVC_{z,t,i} = VCT_z - VC_{z,t,i} \qquad \forall z \in Z, \quad \forall t \in T, \quad \forall i \in I \qquad \text{Eq. (13)}$$

where $VCT_{z,t}$ = water volume change target (m$^3$) in tank $z$; and $VC_{z,t,i}$ = water volume change (m$^3$) in tank $z$.

The weighting factor $w$ in Eq. (1) is needed to scale the two objectives (energy cost and water volume change in tanks) onto the same unit of measurement so they can be added up. The weighting factor is usually equal to the target value of the objective that is multiplied by the weight factor (Romero 1991), in this case the weight factor is equal to the target value of tanks water volume change $VCT_z$. Since $VCT_z$ is required to be an optimistic value, it could be set to zero. However, here, the value of $VCT_z$ is set to a small amount of 1 m$^3$, to avoid multiplication by zero. The weighting factor $w$ can be set by a pump scheduler (e.g. control room operator) to reflect his/her attitude toward balancing the two objectives.

To reduce the number of variables and to increase the computational efficiency, we related the change of water volume in tanks to pumps flow and demands. The following equation calculates the water volume change in each tank during each time step:

$$VC_{z,t,i} = \left( \left( \sum_{v=1}^{V} Q_{v,t,i}^{\substack{Max.\\ Speed}} . x_{v,t,i} \right) + \left( \sum_{f=1}^{F} Q_{f,t,i} . x_{f,t,i} \right) - D_{z,t} \right) . S_t \quad \forall z \in Z, \forall t \in T, \forall i \in I \quad \text{Eq. (14)}$$

where $D_{z,t}$ = total demand from tank $z$ during time step $t$ (m$^3$/hr). The first term $Q_{v,t,i}^{Maximum\ Speed} . x_{v,t,i}$ gives the flow of the VSP at the actual speed according to the Affinity Laws. If a pump draws water from tank $z$, then its flow value is negative.

The water volume in each tank is constrained during each time step as shown in the following equation:

$$V_{z,min} \leq \left( \sum_{t=1}^{t} VC_{z,t,i} \right) + V_{z,initial} \leq V_{z,max} \qquad \forall i \in I, \forall z \in Z, \forall t \in T \qquad \text{Eq. (15)}$$

where $V_{z,min}$ = minimum water volume in tank $z$ (m$^3$); $V_{z,initial}$ = initial water volume in tank $z$ (m$^3$); $V_{z,max}$ = maximum water volume in tank $z$ (m$^3$).

The following constraint is used to ensure that the final water volume in each tank is at least equal to the initial one:

$$\sum_{t=1}^{T} VC_{z,t,i} \geq 0 \qquad \forall i \in I, \qquad \forall z \in Z \qquad \text{Eq. (16)}$$

The following mass balance constraint is used in case where there is no tank in a pressure zone (or water system):

$$VC_{z,t,i} = 0 \qquad \forall z \in Z, \qquad \forall t \in T, \qquad \forall i \in I \qquad \text{Eq. (17)}$$

Energy balance constraint is solved implicitly by the hydraulic simulator as will be shown in the next section.

Weighted average chlorine is used to quantify the spatial distribution of chlorine in the demand nodes as follows (motivated by a similar metric used for network water age in Marchi et al. (2014)):

$$WAC = \frac{\sum_j^J \sum_t^T k.Q_{j,t}.C_{j,t}}{\sum_j^J \sum_t^T Q_{j,t}} \qquad \text{Eq. (18)}$$

Where $WAC$ = weighted average chlorine in the network; $Q_{j,t}$ = demand in node $j$; $C_{j,t}$ = chlorine in node $j$; $j$ = node index; $J$ = total number of nodes; and $k$ = constant that equals to 1 if $C_{j,t}$ is above predefine chlorine threshold or 0 otherwise. Nodes with high demand have more impact on the weighted average chlorine. Nodes with chlorine below the predefined threshold reduces the weighted average chlorine.

### ***Scheduling Problem Solution***

The pump scheduling problem defined in the previous section is solved here by using the iterative Extended Lexicographic Goal Programming (iELGP) method, as shown in Fig. 1. The solution process starts by setting the value for energy cost target $ECT$ which needs to be carefully specified. If ECT is set too pessimistically then the resulting solution will be Pareto inefficient. If, on the other hand, ECT is set too optimistically (e.g. set equal to zero) then the method will focus on the energy cost target and will not take into consideration the other target (water volume change in tanks). The way that energy cost target is estimated is shown in the following solution steps:

1- Set iteration index $i = 1$.
2- For each VSP, find its flow and head values at its best efficiency point (BEP) when speed is maximum, then substitute these values in Eq. (8) to calculate $P_{v,t,i}^{Maximum\ Speed}$ and use it in Eq. (4). Each VSP has the same $P_{v,t,i}^{Maximum\ Speed}$ for all time steps in the first iteration.
3- For each FSP, find its flow and head values at its BEP, then substitute these values in Eq. (10) to calculate $P_{f,t,i}$. Each FSP has the same $P_{f,t,i}$ for all time steps in the first iteration.
4- Find the optimum statuses for VSPs and FSPs (i.e. $x_{v,t,1}$ and $x_{f,t,1}$) and the minimum energy cost $EC_1$ using Mixed Integer Linear Programming (MILP), where Eq. (3) is the objective function to be minimized and Eqs. (4), (5), (6), (7), (9), (11), (12), (15), (16), and (17)

are the constraints.

5- Set energy cost target $ECT$ equals to energy cost $EC_1$ which is found in solution step 4. As can be seen, energy cost target equals to the optimum energy cost when all pumps have flow values at their BEP. This is an ideal optimistic value that is not realistic.

The optimum pumps' statuses ($x_{v,t,1}$ and $x_{f,t,1}$) which are found in step 4 are based on unreliable flow values. The flow values and the optimum pumps' statuses are corrected in an iterative way as shown in the following steps:

6- Set time step index $t$ = 1.

7- Apply the optimum pumps' statuses ($x_{v,t,i}$ and $x_{f,t,i}$) during time step $t$ on a hydraulic simulator for the water network which needs to be optimized.

8- Retrieve flow of VSPs $Q_{v,t,i}^{Actual\ Speed,\ \ Simulator}$ and FSPs $Q_{f,t,i}^{Simulator}$ from the hydraulic simulator. Find $Q_{v,t,i}^{Maximum\ Speed,\ \ Simulator}$ using affinity laws.

9- For all VSPs at time step $t$, if percentage differences between $Q_{v,t,i}^{Maximum\ Speed,\ \ Simulator}$ and $Q_{v,t,i}^{Maximum\ Speed}$ (which were used in Eq. (8) to calculate $P_{v,t,i}^{Maximum\ Speed}$ in the current iteration $i$) are all less than 1%, then move to step 12. The 1% tolerance was selected after limited sensitivity analysis on 3 case studies (2 in Abdallah and Kapelan (2017) and 1 in this paper). These case studies have different topologies, demand patterns, pipes and pumps characteristics. The threshold value proposed results in convergence in the three case studies. Having said this, if a smaller tolerance value is used, then the number of iterations will increase (without significant improvement in the final optimal solution) and, in the worst, case scenario, the iELGP method may not converge to an optimal solution. This tolerance may have to be adjusted for other case studies.

10- If percentage difference between $Q_{v,t,i}^{Maximum\ Speed,\ \ Simulator}$ and $Q_{v,t,i}^{Maximum\ Speed}$ for at least one of the VSPs $v^*$ is more than 1%, then substitute $Q_{v,t,i}^{Maximum\ Speed}$ with

$Q_{v,t,i}^{Maximum\ Speed,\ \ Simulator}$ in Eq. (8), and Eq. (14) for pump $v^*$ and for all other pumps that are running in parallel and in series with pump $v^*$ in time step $t$.

11- Find heads and efficiencies for all VSPs that change their $Q_{v,t,i}^{Maximum\ Speed}$ values in solution step 10 using their head and efficiency curves, then recalculate their $P_{v,t,i}^{Maximum\ Speed}$ using Eq. (8). Move to step 13.

12- For all FSPs at time step $t$, if percentage differences between $Q_{f,t,i}^{Simulator}$ and $Q_{f,t,i}$ (which were used in Eq. (10) to calculate pump power $P_{f,t,i}$ in current iteration $i$) are all less than 1%, and if $t$ is not the last time step, then move to the next time step $t = t + 1$ and go back to step 7. If $t$ is the last time step, then move to step 17.

13- If percentage difference between $Q_{f,t,i}^{Simulator}$ and $Q_{f,t,i}$ for at least one of the FSPs $f^*$ is more than 1%, then substitute $Q_{f,t,i}$ with $Q_{f,t,i}^{Simulator}$ in Eqs. (10), and (14) for pump $f^*$ and for all other pumps that are running in parallel and in series with pump $f^*$ in time step $t$.

14- Find heads and efficiencies for all FSPs that change their $Q_{f,t,i}$ values in solution step 13 using their head and efficiency curves, then recalculate their $P_{f,t,i}$ using Eq. (10).

15- Find the optimum statues ($x_{v,t,i}$ and $x_{f,t,i}$) for all pumps during all time steps and find the minimum deviation variables ($PEC_i$, $PVC_{z,t,i}$, and $NVC_{z,t,i}$) using GP, where Eq. (1) is the objective function and Eqs. (2), (3), (4), (5), (6), (7), (9), (11), (12), (13), (14), (15), (16), (17) are the constraints.

16- Start new iteration $i = i + 1$ and go back to step 6.

17- If $t$ is the last time step, then iteration will terminate.

18- Find chlorine concentration at each demand node by running the water quality simulator.

The solution in the last iteration has the minimum energy cost and water volume change in tanks. The flow chart for the previous steps is shown in Fig. 1.

A pump scheduling program is developed in *MATLAB R2011b* computer software. The iELGP-based optimiser calls the hydraulic simulator *EPANET 2.0* to do the hydraulic and water quality calculations, and the MILP solver *lp_solve 5.5.2.0* (Berkelaar et al. 2016) to do the optimisation.

## Case Study

### *Description*

The iELGP method is applied here on the same, real-life C-Town network that was used in Price and Ostfeld (2016). The EPANET input file for this network is available online (WDSA 2014). All of the following descriptions and assumptions for C-Town network were used in Price and Ostfeld (2016). This enables a fair comparison of solutions to be made. The C-Town network is shown in Fig. 2 and it consists of 1 water source, 11 FSPs, 7 tanks, 388 junctions, and 1 valve that is always opened. All pumps are assumed a fixed efficiency of 70%.

The residual chlorine is fixed to 0.50 mg/l upstream of all pumps and at tanks T2 and T6 at all times. Other tanks have initial chlorine value of 0 mg/l. Water mixing in tanks is assumed to be instantaneous and complete. The first order bulk decay rate is set to -0.55 mg/l/day and the first order wall decay rate is set to 0 m/day. The minimum required residual chlorine in all demand nodes is 0.28 mg/l.

The network is optimized for 1 week which is divided into 168 equal time steps of 1 hour length. Time step length in the hydraulic simulation is 1 hour and in the water quality simulation is 5 minutes. The hourly electrical tariff is shown in Fig. 3.

Three cases of C-Town network are optimized. In case I, the minimum required residual chlorine of 0.28 mg/l at demand nodes is reached by reducing tanks' maximum levels (the second term in Eq. (1) is set equal to zero in Case I), as in Case 1e of Price and Ostfeld (2016). This was done to compare the performance of the iELGP method to the graph theory method of Price and Ostfeld (2016).

After careful study of the C-Town network, it was found that demand nodes which can be supplied from tank T3 have very low residual chlorine. Thus, in cases II and III, the minimum required residual chlorine at all demand nodes is reached by minimizing tank T3 inlet and outlet flow rate. In other words, tank T3 is allowed to loose and gain water at minimum rates, to increase chlorine in its related demand nodes and, at the same time, to keep its water fresh. This was done to test the effect of minimizing tanks flow on demand nodes chlorine and compare it to the effect of minimizing tanks maximum water level (Case I).

In addition, in Cases I and II only FSPs are used (as it was done in Case 1e of Price and Ostfeld (2016)) whilst in Case III pumps P1, P2, and P3 are assumed to have variable speeds (with respective maximum speeds set equal to their fixed speeds in Case 1e of Avi and Ostfeld (2016), Case I and Case II). This enables to analyse the potential benefits of using variable speed pumps in Case III.

In all cases, initial water level in each tank is set equal to half of that tank's maximum water level in Case 1e of Price and Ostfeld (2016). Minimum water level in all tanks in all cases is 0 m.

The computer used in Price and Ostfeld (2016) is based on the Intel® Core™ i7-3770 CPU running at 3.40 GHz and the RAM available is 8 GB. The computer used in this research is based on the Intel® Core™ i7-3612 QM CPU running at 2.10 GHz and the RAM available is 8 GB.

## ***Results and Discussion***

The results obtained for each of the three cases analysed are summarised in Table 1.

As it can be seen from Table 1, in Case I, the optimal pump schedule identified by using the iELGP method has lower energy cost of 381.10 $/day than the corresponding solution identified by Price and Ostfeld (2016) which has the energy cost of 395.40 $/day. However, the latter solution has lower total number of pump switches (230) than the former solution (342). This means that there is a trade-off between energy cost and total number of pump switches. The iELGP method identifies solution with a lower energy cost but also with a higher number of pump switches. This is because the iELGP method allows pumps to run for a fraction of each time step, unlike the approach proposed by Price and Ostfeld (2016). Note that both methods have not constrained the number of pump switches. This is because reducing the number of pump switches increases water age and hence reduces residual chlorine in the network (Price and Ostfeld 2016). Having said this, it is possible to reduce the number of pump switches in iELGP by increasing the length of time steps (instead of one hour) and allowing pumps to start only once during a time step. This was already proved in Abdallah and Kapelan (2017).

The optimum tanks' levels obtained by the iELGP method for Case I are shown in Fig. 3. As it can be seen from this figure, as expected, tanks' levels increase (i.e. tanks refill) during low electrical tariff periods and decrease (i.e. empty) during high electrical tariff periods. Tanks' final levels are also equal to or above their initial levels meaning that all tanks in the analysed network are balancing well. Tanks T2 and T6 have high water levels most of the time because they have lower elevation than respective parallel tanks T1 and T7. Having high water levels in tanks T2 and T6 most of the time increases their water age and decreases their chlorine. To avoid that, chlorine is set to 0.5 mg/l at tanks T2 and T6 at all times, as mentioned previously.

Fig. 4 shows the hourly tank T3 levels for Cases I, II and III and tank T3 chlorine concentration in Cases II and III. As it can be seen from this figure, water level in tank T3 in Case I has many hikes (tank drains and refills frequently). This is because tank T3 maximum level is reduced by 85% to have minimum chlorine of 0.28 mg/l at nearby demand nodes. In contrast, tank T3 level in Case II is almost steady and it is smooth in Case III when compared to Case I. This is because in Cases II and III, the 0.28 mg/l minimum residual chlorine in the network was reached by minimizing tank T3's inlet/outlet flow. In Cases II and III, pump P4 (which supplies tank T3) starts at the beginning of every time step and stops before the end of each time step. This is to provide sufficient water supply to demand nodes and to, at the same time, avoid storing excess water in T3. Table 1 shows that pump P4 in Cases II and III has the highest number of pump switches. This causes tank T3 to have good chlorine range in Cases II and III as shown in Fig. 4.

As shown in Table 1. VSPs benefits Case III when compared to Case II. The number of switches for pumps P1, P2, and P3 are reduced from 34 to 6 and the total energy cost is reduced from 394.60 to 385.04 $/day.

Fig. 5 shows tank T1 water level and pumps P1, P2, P3 status/speed in Cases II and III. As it can be seen from this figure, FSPs P1, P2, and P3 in Case II start with the maximum constant speed during low electrical tariff and stop during high electrical tariff. However, in Case III, VSPs P1, P2, and P3 are running all the time (except during time steps 163, 164, and 167) and at the minimum relative speed of 0.70 (except for few time steps where relative speed is 0.80). Additionally, when parallel VSPs P1, P2, and P3 are running in Case III, they are running at the same speed, to equally share the load and reduce energy cost, as mentioned previously.

The above mentioned difference in pumps P1, P2, and P3 running between Cases II and III makes the water level of tank T1 (which is supplied by pumps P1, P2, P3) different in Cases II and III. Tank T1 water level in Case II increases steeply during low electrical tariff and decreases steeply during high electrical tariff. This is because pumps P1, P2, and P3 in this case start (with the maximum constant speed) during low electrical tariff and stops during high electrical tariff. Tank 1 level in Case III increases during the peak tariff hours because in this case VSPs 1, 2, and 3, which supply water to this tank, are running during the peak tariff hours. However, FSPs 4, 5, 6, 7, 8, 9, 10 and 11, which are drawing water from the same tank, are not running during the peak tariff hours.

The above mentioned running behaviour of pumps in Case III increases the number of water level cycles in tank T1 and allows water to reside in tank T1 for less time than in Case II. Thus, tank T1 have lower water age and higher residual chlorine in Case III than in Case II. Additionally, having the source pumps P1, P2, and P3 running almost all the time in Case III at minimum speed of 0.70 provides more fresh water for the whole network all the time than in Case II where pumps P1, P2, and P3 are running at maximum speeds during low electrical tariff (and not running during the high electrical tariff). As a consequence, the weighted average network chlorine in Case III (0.429 mg/l) is slightly higher than that in Case II (0.419 mg/l). The improved water quality represents an additional advantage of using VSPs, i.e. in addition to previously mentioned lower energy cost and lower number of pump switches.

Table 1 also shows that the iELGP method is highly computationally efficient, as evidenced by short optimisation times required in all three cases to generate hourly pump schedules for a whole week.

Out of the three cases analysed, Case III requires the largest computational time to identify optimal pump schedule. This is because of the time consuming Branch and Bound method that is used in this case to optimise the operation of VSPs P1, P2, and P3. Note also that in all three cases (I, II, and III), *Epanet 2.0* reinitializes hydraulic simulations to the first time step in each iteration. This consumes a lot of computational time (Price and Ostfeld 2015) and avoding this could further reduce the total computational time required.

### *Further Remarks*

All pumps in the C-Town network case study were assumed a fixed efficiency of 70%, for the sake of simplicity. However, iELGP optimisation method can deal with variable efficiencies (Abdallah and Kapelan 2017) and unlike several existing pump scheduling methods (Chen and Coulbeck 1991; Price and Ostfeld 2015) which assume fixed efficiency for pumps.

It is required to know in advance which tanks deteriorates chlorine and water age in the demand nodes by running a water quality simulation. The deterioration depends on many things such as tanks' sizes, how far tanks are from their supply pumps and demand pattern downstream the tanks'.

As it can be further seen from Table 1, the energy cost in Case I is lower than the corresponding energy costs in Cases II and III. This is because in Cases II and III, there is no energy saving made in pump P4 which supplies tank T3, because it starts and stops during all time steps including high electrical tariff time steps. Additionally, the weighted average network chlorine in Case I is 0.435 mg/l, while it is 0.419 mg/l in Case II and 0.429 mg/l. This is because in Case I tanks' maximum levels are reduced to have minimum chlorine of 0.28 mg/l everywhere in the network, while in Cases II and III only tank T3 flow was minimized to have minimum chlorine of 0.28 mg/l everywhere in the network. If tanks flow other than tank T3 flow are also reduced in Cases II and III, and if weight factors $w$ for tanks' flow are reduced, then Cases II and III might have better energy cost and weighted average chlorine than Case I. Thus, although Case I gives lower energy cost and higher weighted average chlorine than Cases II and III, one cannot conclude that reducing tanks' maximum level is better than minimizing tanks' flow in terms of energy cost and chlorine.

Minimizing tank T3 flow in Cases II and III did not decrease the residual chlorine in tank T3 as shown in Fig. 4.  However, there is possibility in other cases studies that minimizing tanks flow will reduce residual chlorine in the tanks because water age in tanks will increase. This problem can be solved by reducing the weight factor $w$ in the objective function Eq. (1). This will decrease the weight of water volume change in the objective function and make the optimisation method focus more on minimizing the energy cost; thus giving more freedom to tanks to increase and decrease their water levels based on electrical tariff. In general, the value of the weight factor $w$ needs to be carefully chosen due to the sensitivity of the objective function Eq. (1) to this factor and to ensure identifying efficient Pareto optimal solutions (Cohon 1978; Walski, et al. 2003, Jones and Tamiz 2010). The two objectives (energy cost and water volume change in tanks) are inversely proportional to each other, i.e. reducing energy cost by running pumps during low tariffs and stopping pumps during high tariffs causes high water volume changes in tanks and reduces chlorine in the network. In contrast, running pumps based on demand only regardless of electrical tariff increases energy cost and reduces water volume changes in tanks (improves chlorine in the network). So, once the value of the weighting factor $w$ is selected, then the minimum chlorine concentration should be fulfilled by the optimal solution every time the optimisation method is run. This, of course, does not hold if there is a major change in demand patterns or if the network configuration changes. In this case, the value of the weighting factor should be changed to reflect these changes.

Several research works proved that decreasing VSP speed (and thus the VSP flow rate) causes decrease in chlorine decay in the water network (Ramos, et al. 2010; Mohammed and Khudiar 2012; Jamwal and Kumar 2016). This is due to the decrease in pipe wall reaction and biofilm removal. However, the above effect of VSPs on chlorine decay does not appear in *EPANET 2.0* water quality simulator because it does not account for mass flux between the water and the pipe wall which depends on the flow rate.

The ability of the iELGP method to find optimal solutions in three different cases (I, II, and III) represents a good sensitivity test that proves the robustness of this method under different conditions in the network. Additionally, note that, unlike many other stochastic pump scheduling methods (especially the ones based on Evolutionary Algorithms, e.g. Wu and Zhu (2009) and Hashemi et al. (2013)), the iELGP method does not have parameters that require tuning before running the optimisation and it is a deterministic optimisation method that gives the same solution for the same initial conditions every time the optimisation is run.

As stated in Abdallah and Kapelan (2017), the iELGP pump scheduling method does not guarantee obtaining the minimum required pressures at demand nodes because these are not constrained. The iELGP method assumes that the water distribution network is designed in such a way that minimum required pressures are always provided under normal operating conditions, i.e., regardless of tanks' levels or pumps running. This potential drawback can be overcome by increasing the minimum water volume in Eq. (15) only for tanks that supply demand nodes which are expected to have pressure below the minimum required pressure during the optimization period.

Water demand changes from day to day and hence can affect the identification of optimal pump schedules. This can be overcome by linking a demand forecaster to the pump scheduling methodology. However, it was not preferred to do so in this paper as it would shift the focus and also make the paper too long.

## Conclusions

A new pump scheduling method based on the iELGP optimisation method is developed and presented here. The method aims to optimize energy cost and water quality (residual chlorine) in large scale multi-tank water networks that have mixture of variable and fixed speed pumps. The method is tested and validated on the real-life C-Town network. The results obtained by using the iELGP method are compared with the results obtained by the pump scheduling introduced and tested on the same network by Price and Ostfeld (2016). The key findings obtained are as follows:

1. The iELGP based methodology is capable of determining optimal, low cost pump schedules whilst trading-off energy costs and water quality. The optimal schedules for both fixed and variable speed pumps can be generated in a computationally very efficient manner. Given this, the iELGP method has potential to be applied to real-time scheduling of pumps in larger,

water distribution networks and without the need to simplify the respective hydraulic models or replace these with surrogate models in the form of ANN or otherwise.

2. The comparison of the iELGP and Price and Ostfeld (2016) graph theory based method shows that the iELGP method can identify pump schedules with lower energy cost and in a computationally more efficient manner (albeit at the cost of increased number of pump switches, even though neither of the two methods constrained this).
3. Two different approaches were used to improve water quality (i.e. increase residual chlorine) in the analysed C-Town network whilst scheduling pumps, by reducing tanks' maximum water levels and by minimizing tanks' in/out flows. Both approaches proved their ability to improve water quality through pump scheduling without the need to change chlorine dosing set-point or add chlorine boosters.
4. When comparing the pump schedules obtained by using fixed and variable speed pumps at the source of the C-Town network, it was found that using variable speed pumps reduces the total cost of energy used for pumping, it reduces the total number of pump switches, and it also improves the water quality by increasing the weighted average residual chlorine in the network.

Future work should include scheduling of network valves (in addition to pumps) and finding better approach to determine the weight factor used to combine the two objectives into a single-objective pump scheduling problem.

## ***Notation***

*The following symbols are used in this paper:*

$b_{v,t,i}$ = binary variable that is equal to zero when pump is not running and equal to one when pump is running;

$C_{j,t}$ = chlorine in node $j$;

$CV$ = total number of possible VSPs combinations in a group of parallel identical VSPs;

$cv$ = index of combined VSP;

$D_{z,t}$ = total demand from tank $z$ during time step $t$ ($m^3$/hr);

$E_t$ = cost of electricity for given time step $t$ (£/KWh);

$EC_i$ = energy cost at iteration $i$ (£);

$ECT$ = energy cost target (£);

$F$ = total number of FSPs;

$f$ = FSP index;

$G$ = total number of pumps in a group of parallel pumps;

$g$ = pump index in a group of parallel pumps;

$h_{v,t,i}^{Maximum\ Speed}$ = head (m) of pump $v$ running at maximum speed;

$h_{f,t,i}$ = head (m) of pump $f$;

$I$= total number of iterations;

$i$= iELGP iteration index;

$J$ = total number of nodes;

$j$ = node index;

$k$ = constant that equals to 1 if $C_{j,t}$ is above predefine chlorine threshold or 0 otherwise.

$NVC_{z,t,i}$ = negative deviation variable for water volume change in tank $z$ ($m^3$);

$PEC_i$ = positive deviation variable for energy cost at iteration $i$ (£);

$PVC_{z,t,i}$ = positive deviation variable for water volume change in tank $z$ ($m^3$);

$P_{v,t,i}^{Actual\ Speed}$ = VSP power at actual speed;

$P_{f,t,i}$ = FSP power;

$P_{v,t,i}^{Maximum\ Speed}$ = VSP power at maximum speed;

$Q_{v,t,i}^{Maximum\ Speed}$ = flow rate ($m^3$/h) of pump $v$ running at maximum speed;

$Q_{f,t,i}$ = flow rate ($m^3$/h) of pump $f$;

$Q_{j,t}$ = demand in node $j$;

$S_t$ = time step length (hr);

$s$ = the slope of the regression line which is equal to 2.1850;

$T$ = total number of time steps;

$t$ = time step index;

$VCT_{z,t}$ = water volume change target ($m^3$) in tank $z$;

$VC_{z,t,i}$ = water volume change ($m^3$) in tank $z$;

$V_{z,min}$ = minimum water volume in tank $z$ ($m^3$);

$V_{z,initial}$ = initial water volume in tank $z$ ($m^3$);

$V_{z,max}$ = maximum water volume in tank $z$ ($m^3$);

$V$ = total number of VSPs;

$v$ = VSP index;

$WAC$ = weighted average chlorine in the network;

$w$ = weighting factor;

$x_{f,t,i}$ = decision variable denoting pump *f* status;

$x_{v,t,i}$ = decision variable denoting relative speed of VSP v at time t and iteration *i;*

$y$ = the y-intercept of the regression line which is equal to 1.2176;

$Z$ = total number of tanks;

$z$ = tank index;

$\gamma$ = specific weight of water ($kN/m^3$);

$\eta_{v,t,i}^{Maximum\ Speed}$ = efficiency of pump v running at maximum speed;

$\eta_{f,t,i}$ = efficiency of pump *f*;

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## *List of tables*

**Table 1.** Data and optimisation results for different cases of C-Town water network

**Table 1.** Data and optimisation results for different cases of C-Town water network

| Optimisation Method | Graph theory Case 1e from Price and Ostfeld (2016) | iELGP Case I | iELGP Case II | iELGP Case III |
|---|---|---|---|---|
| Reaching the 0.28 mg/l minimum residual chlorine | By reducing tanks’ maximum level: T1 by 65%, T2 by 30%, T3 by 85%, T4 by 15%. These percentages were found by Price and Ostfeld (2016) and fixed before optimisation. | | By minimizing inlet and outlet flow of tank T3 only. | |
| Tank’s Maximum Water Level (m) | | | | |
| T1 | 2.28 | | 6.50 | |
| T2 | 4.13 | | 5.90 | |
| T3 | 1.01 | | 6.75 | |
| T4 | 4.00 | | 4.70 | |
| T5 | 4.50 | | | |
| T6 | 5.50 | | | |
| T7 | 5.00 | | | |
| Pump speed | Fixed | Fixed | Fixed | Fixed except P1, P2, P3 |
| Optimisation Results | | | | |
| Optimum energy cost ($/day) | 395.40 | 381.10 | 394.60 | 385.04 |
| Computation time (min) | 17.2 | 12.3 | 11.9 | 22.7 |
| Weighted average network chlorine (mg/l) | Information not available | 0.435 | 0.419 | 0.429 |
| Pump switches | | | | |
| P1 | 8 | 12 | 13 | 2 |
| P2 | 1 | 33 | 13 | 2 |
| P3 | 17 | 10 | 8 | 2 |
| P4 | 58 | 93 | 168 | 167 |
| P5 | 3 | 0 | 0 | 0 |
| P6 | 31 | 54 | 46 | 33 |
| P7 | 18 | 27 | 17 | 23 |

| | | | | |
|---|---|---|---|---|
| P8 | 42 | 58 | 47 | 34 |
| P9 | 16 | 0 | 1 | 0 |
| P10 | 21 | 50 | 41 | 28 |
| P11 | 15 | 5 | 3 | 10 |
| Total | 230 | 342 | 367 | 301 |

## *List of figures*

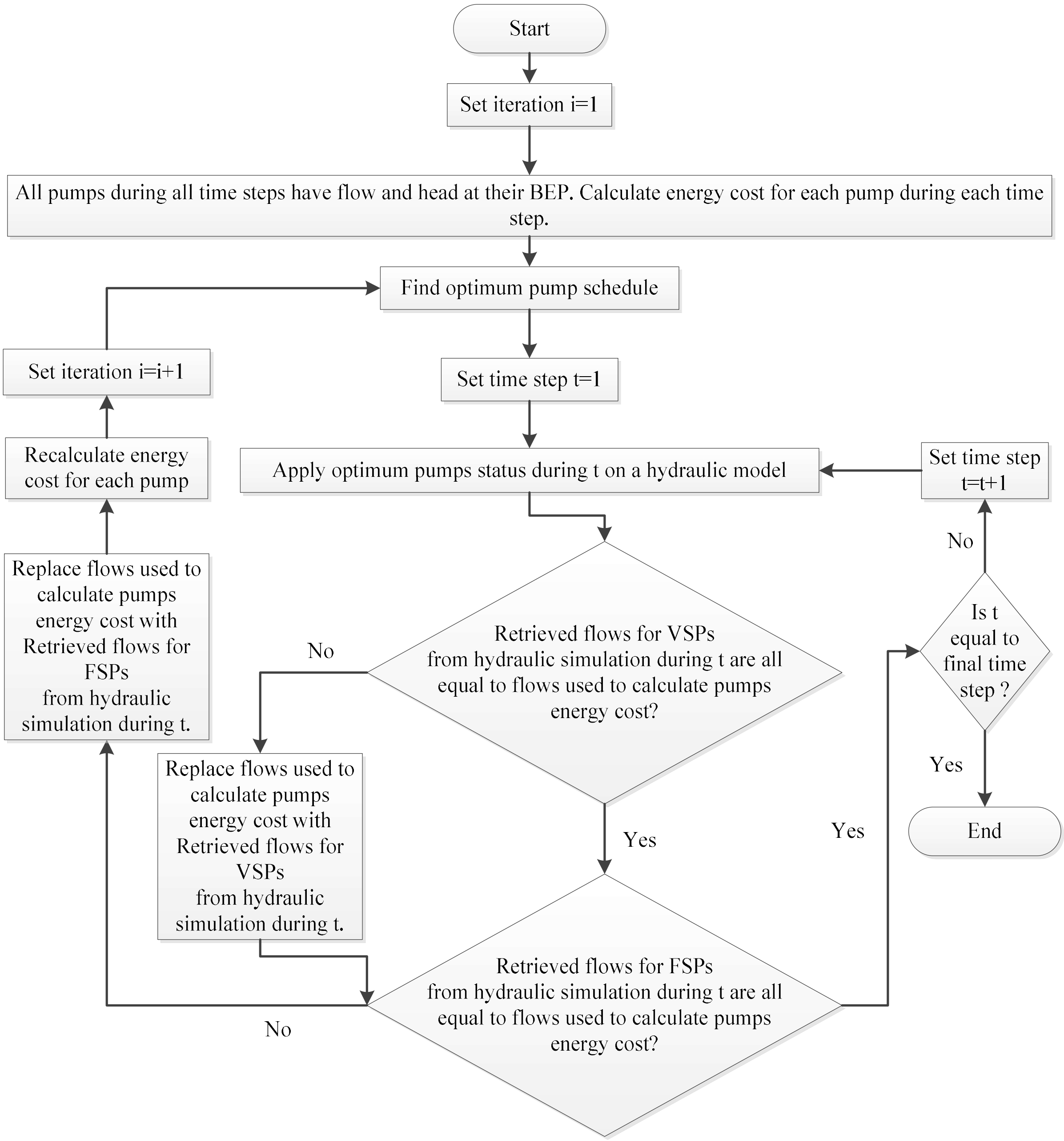

**Fig. 1.** Flow chart for iELGP pump scheduling method

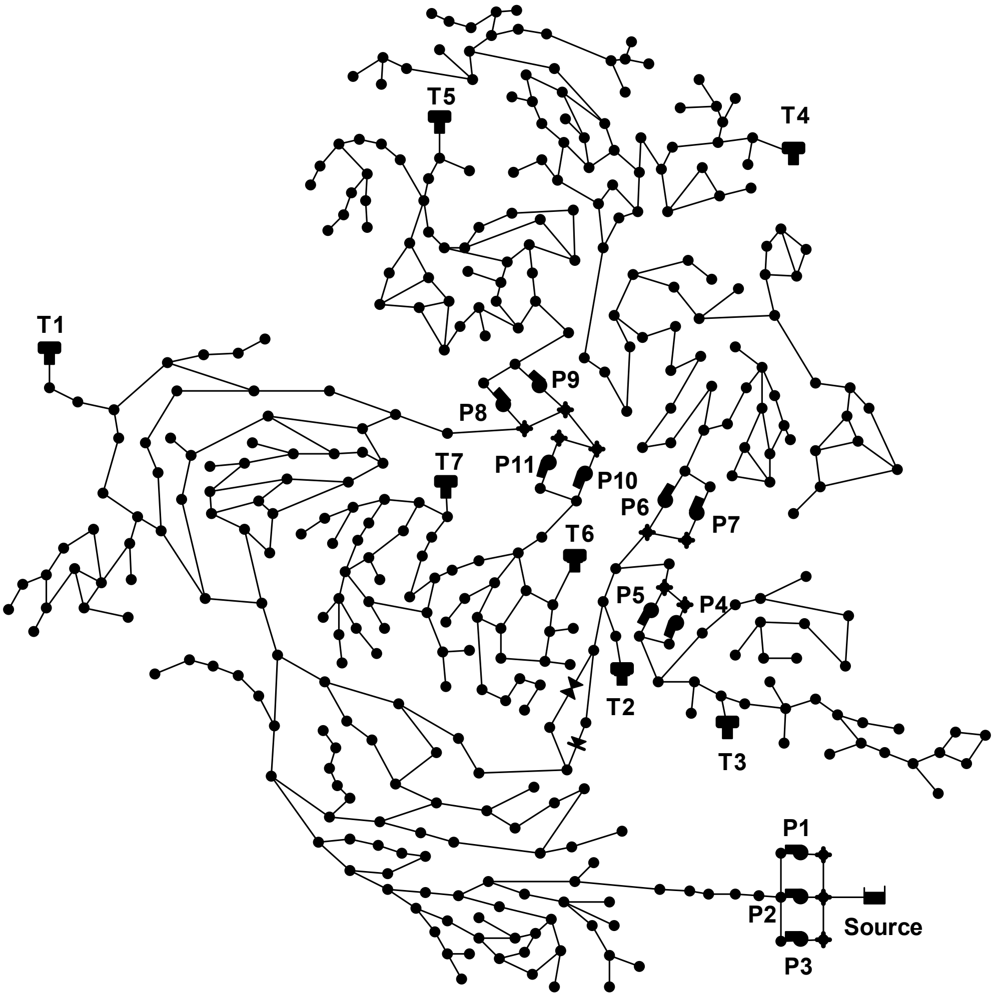

**Fig. 2.** C-Town Network (adapted from Price and Ostfeld (2016))

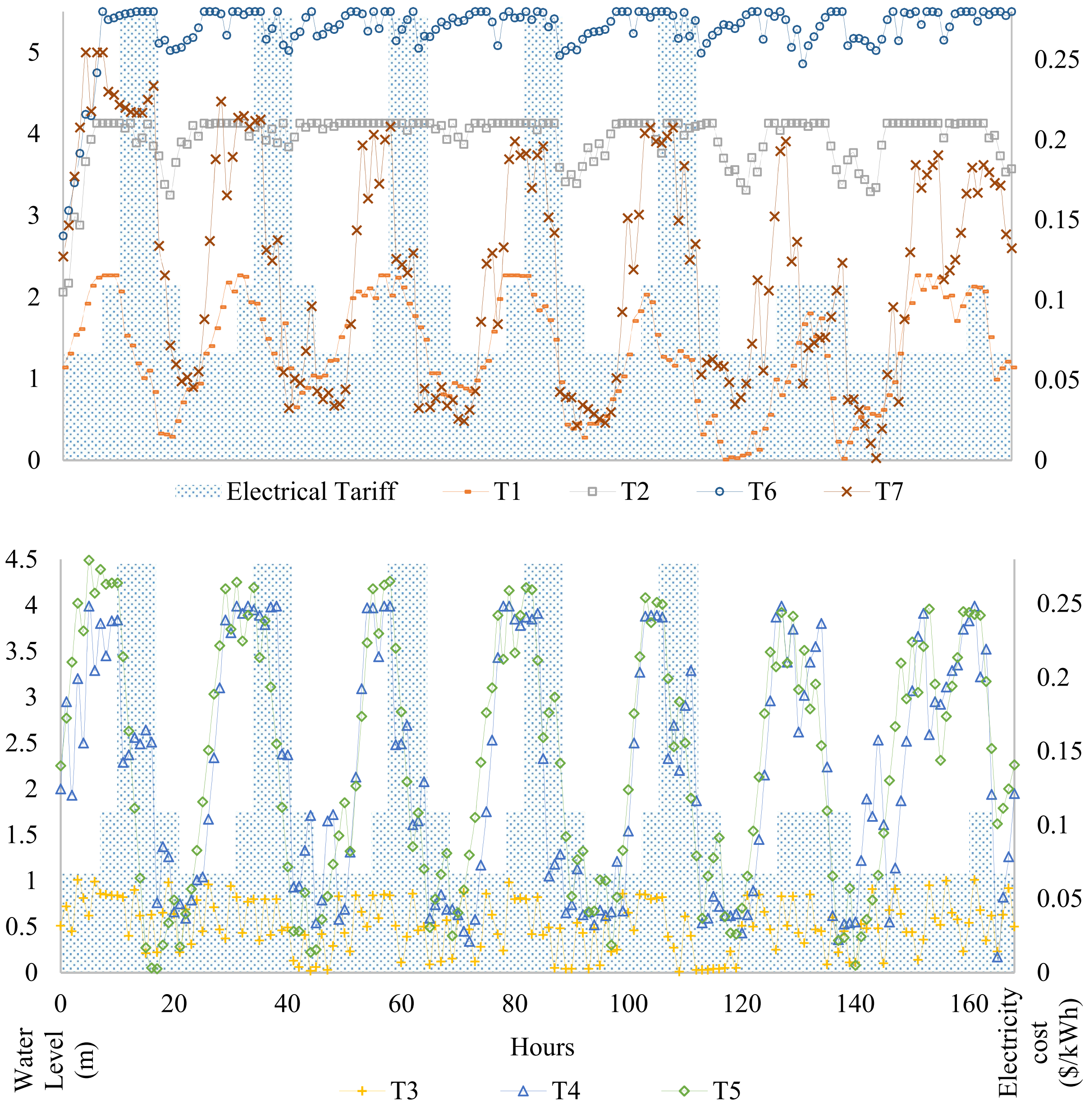

**Fig. 3.** Electrical tariff and optimum tanks' levels for Case I

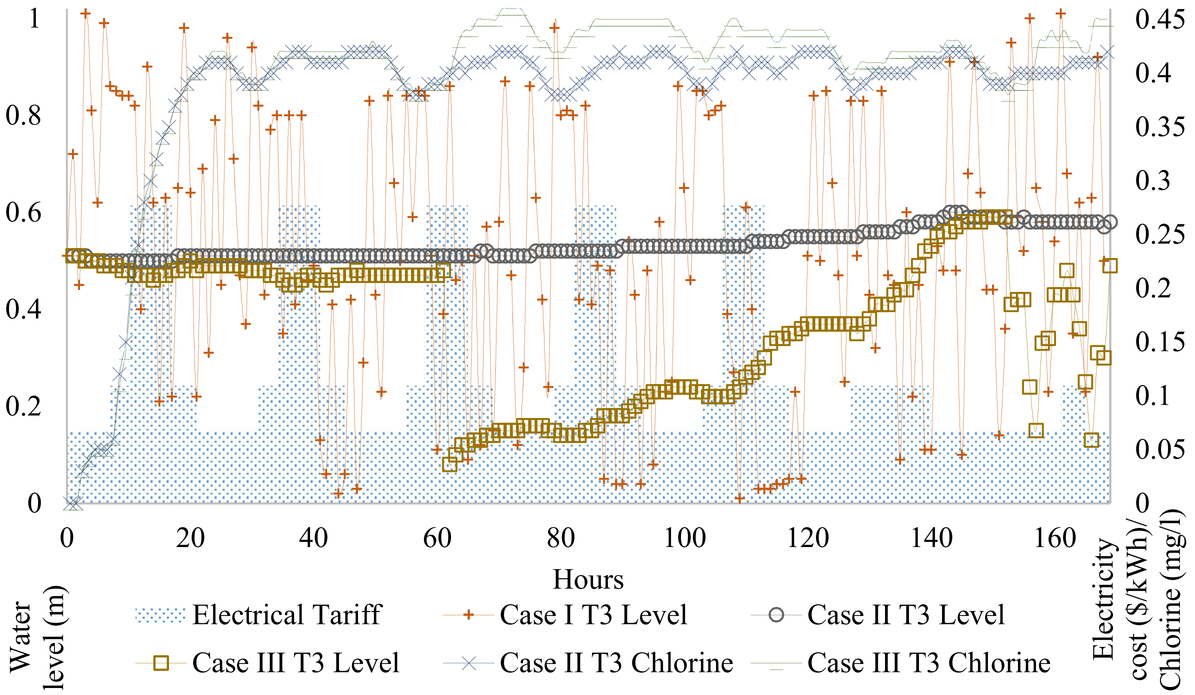

**Fig. 4.** Optimum water level for tank T3 in Cases I, II, and III and residual chlorine in tank T3 in Cases II and III

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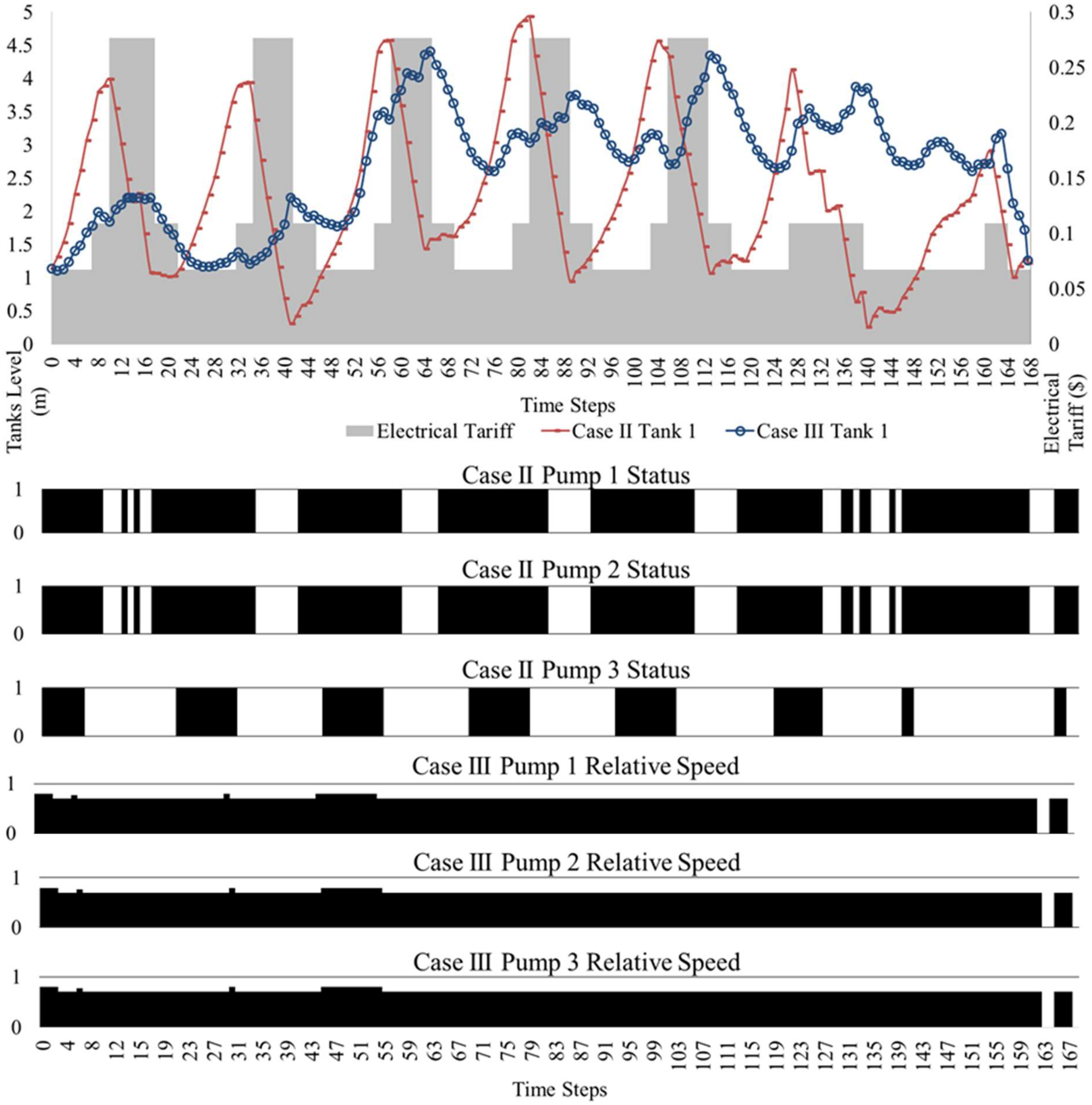

838 **Fig. 5.** Tank T1 water level and pumps P1, P2, P3 status/relative speed in Cases II and III

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