College of Engineering, Mathematics and Physical Sciences

# Pump Scheduling for Optimised Energy Cost and Water Quality in Water Distribution Networks

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I certify that all material in this thesis which is not my own work has been identified and that no material has previously been submitted and approved for the award of a degree by this or any other University.

Signature: …………………

# Abstract

Delivering water to customers in sufficient quantity and quality and at low cost is the main driver for many water utilities around the world. One way of working toward this goal is to optimize the operation of a water distribution system. This means scheduling the operation of pumps in a way that results in minimal cost of energy used. It is not an easy process due to nonlinearity of hydraulic system response to different schedules and complexity of water networks in general.

This thesis reviewed over 250 papers about pump scheduling published in the last 5 decades. The review revealed that, despite a lot of good work done in the past, the existing pump scheduling methods have several drawbacks revolving mainly around the ability to find globally optimal pump schedules and in a computationally efficient manner whilst dealing with water quality and other complexities of large pipe networks.

A new pump scheduling method, entitled iterative Extended Lexicographic Goal Programming (iELGP) method, is developed and presented in this thesis with aim to overcome above drawbacks. The pump scheduling problem is formulated and solved as an optimisation problem with objectives being the electricity cost and the water age (used as a surrogate for water quality). The developed pump scheduling method is general and can be applied to any water distribution network configuration. Moreover, the new method can optimize the operation of fixed and variable speed pumps.

The new method was tested on three different case studies. Each case study has different topography, demand patterns, number of pumps and number of tanks. The objective in the first and second case studies is to minimise energy cost only, whereas in the third case study, energy cost and water age are minimized simultaneously. The results obtained by using the new method are compared with results obtained from other pump scheduling methods that were applied to the same case studies. The results obtained demonstrate that the iELGP method is capable of determining optimal, low cost pump schedules whilst trading-off energy costs and water quality. The optimal schedules can be generated in a computationally very efficient manner. Given this, the iELGP method has potential to be applied in 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.

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I am indebted to my parent for caring and raising me up. I owe them infinite appreciation for directing me. Thanks to my wife who stands with me during every moment. The completion of my Ph.D. journey would not be possible without her continuous support and love.

نَرْفَعُ دَرَجَاتٍ من نشَاءُ وَفَوْقَ كُلِّ ذِي عِلْمٍ عَلِيمٌ (76)

We raise in rank whomever We please, and above every man of knowledge is One who knows best (76)

The Holy Qur’an

Chapter (12): Joseph

*To my sweet daughters*

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## List of Abbreviations

| | |
|---|---|
| ACO | Ant Colony Optimisation |
| ANN | Artificial Neural Networks |
| FSP | Fixed Speed Pump |
| EPS | Extended Period Simulation |
| GA | Genetic Algorithm |
| HGA | Hybrid Genetic Algorithm |
| iELGP | iterative Extended Lexicographic Goal Programming |
| PSP | Pump Scheduling Problem |
| PSM | Pump Scheduling Method |
| VSP | Variable Speed Pump |
| WDS | Water Distribution System |

# Chapter 1: Introduction

The introduction of this thesis starts by outlining the problem that motivates the candidate to do this research. The proposed solution to that problem has several challenges which are listed. After that, the contribution of this research in water management field is presented. The objectives of this thesis and the research questions are then set-up. The structure of this thesis and candidate's publications are provided in the end of this chapter.

## 1.1 Motivation

Energy is the driving force for most life aspects. The world energy consumption is increasing due to population growth and economic development. This is causing serious climatic changes, depletion in energy sources, and increment in energy price (Basheda et al., 2006).

Water Distribution Systems (WDSs) are one of world energy intensive systems, due to energy required to pump water from sources to consumers. A recent review by Lam et al. (2017) shows that energy intensity in WDSs for 17 major cities around the world ranges between 0.01 (in Copenhagen, Denmark) to 0.341 kWh/$m^3$ (in Toronto, Canada). Authors implied that the variation is due to difference in climate, topography of water network, demand patterns, and operation efficiency. In 2011, WDSs in the United States (US) consumed 39.2 billion kWh of electrical energy (Pabi et al., 2013). Over 85% of that electrical energy consumption goes for water distribution pumps. The 39.2 billion kWh corresponded to around 1% of the total electrical energy consumption in US, yet it had increased by 39% since 1996. By 2050, electrical energy consumption in WDSs in US is expected to reach 46 billion kWh (Electric Power Research Institute 2002).

Water, a vital source of natural life, should not only be delivered at low energy cost, but also at good quality. In the early 1990's, water quality issues emerge in regulations to protect public health, reduce health care expenditures, and increase life expectancy (Sedlak 2014). Although water quality improvements is done in treatment plants, bacteria revive again in WDSs when water passes through pipes and tanks. Water utilities use chemicals such as chlorine to disinfect water in their WDSs. However, water disinfection forms disinfection byproducts which become a health concern. Thus, water quality control should not be overcome in WDSs.

## 1.2 Pump Scheduling

There are several approaches to reduce electricity cost and improve water quality in WDSs, such as network rehabilitation, installation of energy harvesting equipment, and installation of new chlorine boosters. However, these approaches have initial costs and long pay pack period. One of the working approach that costs nothing but better management of pumps operations is pump scheduling. Pump scheduling is the process of determining when to start/stop each pump to achieve certain objectives, mainly minimum electricity cost. Other benefits of pump scheduling are listed below:

- Getting a pump schedule for a WDS ahead of time helps to predict what is going to happen in the network in the near future. For example, a pump schedule can tell the operator the time at which he/she needs to start a pump to avoid an expected pressure drop in the network. By doing so, the operator takes actions and mitigates problems in the network before they happen. Thus, increasing the quality of the service.
- Scheduling the operation of pumps helps in scheduling the maintenance program of the pumps. For instance, a pump schedule can tell when it is possible to take a pump for a maintenance in the near future without affecting the water supply in the network.
- Many water pumping stations run continuously and have operators who work in shift cycles. However, there is usually inconsistency between the operators. Pump scheduling is a decision support tool that aligns all operators together regardless of their experience levels. Having consistent operation helps to mitigate human factors and improve controls.
- Pump scheduling can contribute in WDSs development by telling where to build new tanks, or increase pipe sizes, to reduce more energy cost.
- Pump scheduling is useful for demand response in power networks. This is because water can be stored but electricity cannot. When load is low in

the power network, pumps can start and store water in tanks. When the load in the power network is high, pumps can stop and water can be supplied from tanks. Demand response reduces the need to build new power generation plants and electricity substations.

- In this research, we will prove that water age in WDSs can be reduced by altering the operation of pumps without the need to add chlorine boosters or increase dosing. Reducing water age will eventually reduce chlorine disinfection and disinfection byproducts.

The previous benefits of pump scheduling are encouraging, but pump scheduling problem is proven to be a challenging problem. More specifically, in terms of optimisation it is an NP-hard problem (Bagloee et al., 2018). This is due to the following reasons:

- Pump characteristic curve, pipes friction head-loss equation, minor head-loss equation, and reaction kinetics of water quality parameters are all non-linear. This nonlinearity goes to the objective function and constraints of the pump scheduling optimisation problem, which makes it difficult to solve.
- The above mentioned equations are also non-convex (Gleixner et al., 2012; Verleye and Aghezzaf 2013). The non-convexity in the above equations is due to the bi-directional nature of flow in pipes, the discrete choices of pumps, and the continuous changes in system curves due to changes in demands and water level in tanks (D'Ambrosio et al., 2015). Thus, the direction in which pumps' energy cost function is increasing or decreasing is indeterminate. Due to that, it is difficult to put all possible pump combinations in order based on their energy consumption considering all possible demands, tanks levels, flows directions.
- Pump scheduling problem contains mixture of integer decision variables (e.g. on/off pumps' statues) and continuous decision variables (e.g. valve position, pump speed, water production rate). These kind of problems are called mixed-integer and are hard to solve numerically.
  Pump scheduling problem has combinatorial characteristics because we look for the best combination of pumps among a huge number of finite possible combinations (Blum and Roli 2003; Hong et al., 2018). For example, if it is required to find the optimum hourly schedule for three

fixed speed pumps during a day, then we are basically looking for the best pump schedule among $2^{3x24}$ possible solutions.
Solving discrete combinatorial optimisation problem is more difficult than solving continuous real-valued problem. Unlike continuous optimisation problems, in combinatorial optimisation problems gradient and differentiation concepts can't be used. Instead, discrete optimisation methods like integer programming and search algorithms are used. Discrete optimisation methods are time consuming specially for real-life large networks. Thus, in many cases (as will be shown in Chapter 2) pump scheduling problem is sometimes solved as continuous problem (e.g. finding optimum tank level) then as discrete problem (e.g. finding optimum pump schedule for that optimum tank level). Solving an optimisation problem in two levels might reduce the optimality of the solution.

- Evaluation of water quality parameters usually occurs frequently (e.g. every 5 minutes) to detect violations. They are also evaluated over long time horizon (e.g. 1 week) to ensure that a periodic behavior of the water quality parameters is achieved. Thus, having water quality simulation, in addition to water hydraulic simulation will make the problem more computationally expensive.

## 1.3 Thesis Objectives

The overall aim of this thesis is to develop, test/validate and demonstrate advantages of a new, computationally fast yet effective methodology for pump scheduling in real water distribution systems that takes into account water quality aspects in addition to more conventionally addressed costs of pumping energy and maintenance.

The key research questions and related thesis specific objectives are as follows:

1- What are the drawbacks in the existing pump scheduling methods and related gaps in knowledge?

Although there are more than 250 papers about pump scheduling published in the last 5 decades, the problem has not yet been completely solved due to its complexity as mentioned in the previous section. The objectives of this research is to first review the existing pump scheduling methods. The purpose of the review is to reveal the drawbacks in the existing pump scheduling method. The following sub-questions will be answered:

- How water networks were modelled in previous pump scheduling methods?
- How pump scheduling problem was formulated?
- What optimisation methods were used?

2- Can a new pump scheduling method be developed that overcomes the drawbacks of existing pump scheduling methods?

The new pump scheduling method has the following objectives:

- To minimise energy cost in water distribution systems.
- To minimise water age (used as a surrogate for water quality).
- To reduce maintenance cost
- Can be applied on any type of water distribution system that has mixture of fixed and variable speed pumps
- Computationally efficient.

The following sub-questions should be answered:

- What are the assumptions in the new method that might affect the optimality of the solution?
- What are the uncertainties in the new pump scheduling method?

3- How to assess the efficiency and the effectiveness of the new pump scheduling method?

The new pump scheduling method is to be tested on three different case studies that were optimised previously using exiting pump scheduling methods.

The following sub-questions should be answered in the case studies:

- What is the performance of the new pump scheduling method compared to the existing pump scheduling methods?
- How sensitive is the new pump scheduling method to the different conditions in water networks?

- How can uncertainties be dealt with?

## 1.4 Thesis Structure

The next chapter (Chapter 2) includes literature review about pump scheduling in water distribution systems. The first key research question in the previous Section 1.3 and its sub-questions will be answered in chapter 2.

Chapter 3 describes the new pump scheduling methodology that is developed to achieve the research objectives. The second key research question in the previous Section 1.3 and its related sub-question/objectives will be answered/attained in chapter 3.

Chapter 4 presents three case studies that are used to test the effectiveness of the new pump scheduling method. The third key research question in the previous Section 1.3 and its sub-questions will be answered in chapter 4.

Chapter 5 summarise the whole work that has been done in this thesis.

## 1.5 Candidate's Publications

The candidate of this thesis published the following papers:

- Abdallah, M. and Kapelan, Z., (2019). "*Fast Pump Scheduling Method for Optimum Energy Cost and Water Quality in Water Distribution Networks with Fixed and Variable Speed Pumps*," Journal of Water Resources Planning and Management, 10.1061/(ASCE)WR.1943-5452.0001123.
- Abdallah, M. and Kapelan, Z., (2017). "*Iterative Extended Lexicographic Goal Programming Method for Fast and Optimal Pump Scheduling in Water Distribution Networks*," Journal of Water Resources Planning and Management, 10.1061/(ASCE)WR.1943-5452.0000843.

The candidate of this thesis presented in the following conferences:

- Abdallah, M. (2019). *Scheduling the operation of pumps in water distribution systems*. Paper presented at 6th International Conference in Water, Energy, and Environment 26-28 March, Sharjah, UAE.
- Abdallah, M. (2019). *Optimizing the operation of water distribution networks*. Paper presented at Abu Dhabi Future Energy Summit 2019, 14-17 January, Abu Dhabi, UAE.
- Abdallah, M. (2016). *Optimum pump scheduling in water distribution networks*. Paper presented at 14th Computing and Control for Water Industry (CCWI), 7-9 November, Amsterdam, Netherlands.

# Chapter 2: Literature Review

## 2.1 Introduction

The general process of pump scheduling is shown in Figure *1*. It starts by capturing the current status of the network (e.g. water levels in tanks) using field instruments and telemetry. A water demand forecasting method is used to predict the water demand during the next optimisation horizon. The current status of the network and the forecasted water demand are used to update the simulator of the calibrated hydraulic model for the network to be optimised. A pump scheduling method runs to identify the optimum pump schedule. The pump scheduling method could be linked with the hydraulic simulator to validate the possible solutions. The optimum pump schedule is then applied using supervisory control and data acquisition (SCADA).

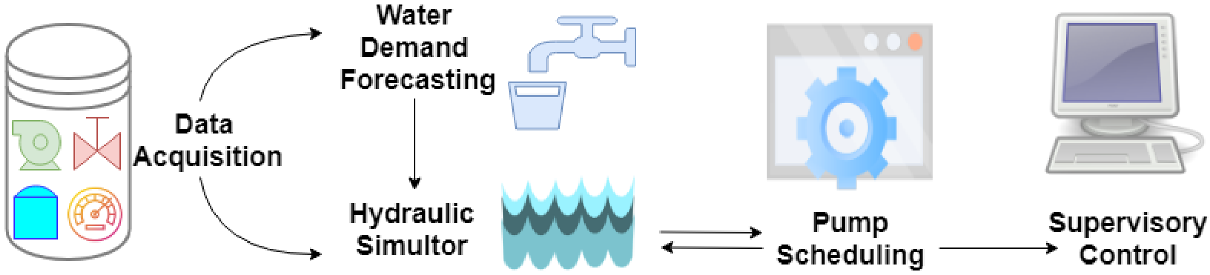


Figure 1. Pump Scheduling Process

This chapter explores more than 250 pump scheduling methods (PSMs) that had been published. These PSMs are different from each other, however they mainly consists of 3 essential modules: the hydraulic and water quality model, the optimisation model, and the optimisation method. The hydraulic model is the tool that describes the behavior of a water distribution system (WDS). The optimisation model consists of objective function, decision variables, and constraints. The optimisation method is the technique that finds decision variables' values which give the best value of the objective function subjected to the constraints. The difference between all existing PSMs is due to the difference in one or more of the previous three modules.

The three modules have also impact on each other. For example, the selection of the optimisation method depends on the hydraulic model and the optimisation model. It is not possible to choose linear programming as an optimisation method to solve the non-linear optimisation model of the pump scheduling problem (PSP) for the non-linear hydraulic equations of a WDS. Thus, when establishing a PSM, the three modules should be developed in parallel.

Each of the three previous modules affect one or more of the following performance indicators for any PSM:

- The optimality of the solution. It is the most important performance measure for a PSM because the main purpose of a PSM is to replace the operation regimes that depend on human factor only with more optimistic and deterministic operation regiems. As mentioned in chapter 1, PSP is discrete optimisation problem. To obtain a global optimum solution, a PSM should explore all possible solutions for a calibrated hydraulic model. Unfortunately, this is not possible in most existing PSMs due to complexity and size of most real WDSs.
- The ability to handle integer and non-integer decision variables since PSP is a mixed integer optimisation problem.
- The feasibility of the solution. Due to approximations in the hydraulic model or in the optimisation model, a PSM might give an optimum solutions that is not feasible (e.g. an optimum solution that makes overflow in tanks, or insufficient pressure at demand nodes). Solution feasibility is vital for water security and consumers satisfaction reasons.
- The computational time. Most of the computational time in pump scheduling methods is consumed by the hydraulic analyses. Many PSMs take long computation time to converge to an optimum solution using normal computers, even for small size hypothetical water networks. Some other PSMs take long time pre-optimisation to tune some parameters or to prepare for offline approximations. Other optimisation methods take long time post-optimisation to transfer implicit decision

variables (e.g. optimum tanks' level) to explicit decision variables (e.g. optimum pump schedule). PSM that takes long time to obtain optimum solution cannot be used for real-time control.

- The applicability of the PSM. A good PSM should be applicable to large size real WDSs that include combination of VSPs and FSPs, multiple tanks, valves, and different topologies.
- The ability to handle different objectives and constraints. This is due to the big trade-off in PSP. For example, minimizing energy cost only might worsen maintenance cost and water quality.

The existing PSMs perform variably on the pervious performance measures. There is no known PSM that performs very well in all of the previous performance measures. This is why PSP has not been solved completely till now. It is still an active field of research that is inspiring many specialists.

The next sections 2.2, 2.3, and 2.4 discusses the three previously mentioned modules and how they were formulated in the previous PSMs. Section 2.5 includes a summary for the whole chapter.

## 2.2 Hydraulic and Water Quality Modelling

Modelling a WDS is the base to optimise its operations. Hydraulic modelling of WDS relies basically on two principles which are conservation of energy and conservation of mass.

Most previous PSMs used extended period simulation (EPS) software for the hydraulic and water quality modelling. The most common EPS software used in PSMs is *EPANET* (López-Ibáñez *et al.,* 2008; Al-Ani and Habibi 2012; Mala-Jetmarova et al. 2014; De Paola *et al.* 2016; Bagloee *et al.,* 2018) because it is an open-source software. Other EPS software that were used in previous PSMs are H2ONET in Boulos *et al.* (2001), KYPIPE in Lansey and Awumah (1994), and Pezeshk and Helweg (1996), WaterGEMS in Moreira and Ramos (2013).

Depending on the optimisation method, EPS software might need to run iteratively to update optimisation model parameters, to check the feasibility of the solution, or to evaluate potential solutions (Brion and Mays 1991;

Giacomello et al., 2012; Mkireb et al., 2019). Many optimisation methods (see section 2.4) require evaluation of large number of possible solutions. Each evaluation requires solving energy and mass balance equations for WDS different components. It is a computationally expensive process (especially for large real-life WDSs) that prevents many existing PSMs from being used for real-time control.

To reduce computation time, surrogate models (also called black box models) were used instead of hydraulic EPS software (Rao and Alvarruiz 2007). Examples of surrogate models that were used to solve PSP are artificial neural networks (ANN) (Shamir et al., 2004; Broad et al., 2005; Martínez et al., 2007; Jamieson *et al.,* 2007; Salomons *et al.,* 2007; Rao and Salomons 2007; Rao *et al.,* 2007; Broad et al., 2010; Behandish and Wu 2014), support vector machine (SVM) (Pasha and Lansey 2014), interpretive structural modelling (Arai *et al.,* 2012). In Wu et al. (2014), ANN was used to replace the water quality EPS.

Model reduction and skeletonisation were also used to decrease dimensionality and increase computational efficiency of PSMs. In Ulanicki and Orr (1991) Jowitt and Germanopoulos (1992), and Burnell *et al.,* 1993, the hydraulic models are linearized and transferred to simple schematic models. In Cembrano et al. (2000), small capacity tanks and pipes were eliminated to facilitate network operation optimisation. In McCormick and Powell (2004), pumps that may interact nonlinearly are grouped to simplify the hydraulic model. In Shamir and Salomons (2008) and Skworcow et al. (2014), different model reduction algorithms were used to reduce the number of nodes and pipes. In Burgschweiger et al. (2009), pipes connected in parallel and series were collapsed into single equivalent pipes. In Sun et al. (2015), a network aggregation method based on simplification and conceptualisation is used to transfer bidirectional pipes in WDSs to one-directional pipes. The full network EPS model can be used to validate the results.

Surrogate models and reduced models are not as accurate as the original model of a WDS. Thus, using them to solve PSP might result in suboptimal or infeasible solution. However, model accuracy is questionable here, since even a fully calibrated hydraulic model is not exactly as the real network. One of the solutions for this problem (hydraulic model is not as accurate as the real WDS) is to use a fast PSM that can be re-run frequently to prevent accumulation of errors that might result from inaccurate models.

In addition to the above, ANN needs to be trained and validated offline which is a computationally intense process. Any major modification in the network configuration or demand patterns required a new training for the original ANN. Thus, calibration of the surrogate model might take longer time than using the original hydraulic model.

Several PSMs relays on explicit mathematical equations instead of EPS software (Ulanicki and Kennedy 1994; Brdys et al., 1995; Cohen et al., 2000a; Cohen et al., 2000b; Cohen et al., 2000c; Sousa et al., 2006; Puleo 2014; Menke et al., 2016). This gives flexibility to relax hydraulic and water quality equations to increase computational efficiency (at the expense of model accuracy). Additionally, it allows to add more operational requirements that are not available in EPS software (e.g. *EPANET* does not calculate correctly energy consumption of VSPs (Marchi and Simpson 2013; Georgescu et al., 2014)). In the following texts, the approximations in the hydraulic and water quality equations in the previous PSMs are explored.

Pipe frictional head-loss in WDSs is calculated using Hazen_Williams or Darcy_Weisbach formulas (Walski *et al.,* 2007; Ormsbee and Walski 2016). These formulas are major cause of nonlinearity in PSP. Hazen-Williams formula was linearised to solve PSP in Van Zyl (2001), Giacomello *et al.,* (2012), Price and Ostfeld (2012b), Schwartz *et al.* (2016), and Oikonomou and Parvania 2018. Darcy-Weisbach formula was relaxed to a convex inequality in Singh and Kekatos (2018), linearised using piecewise linearisation in Verleye and Aghezzaf (2013), smoothed in Burgschweiger et al. (2008) and Burgschweiger et al. (2009), and approximated as a quadratic function in Bonvin et al. (2017).

Energy head-loss through valves, bends, changes in pipe diameter (usually called minor losses) is usually modelled using quadratic function of flow multiplied by minor head-loss coefficient (Walski 2007; AbdelMeguid, 2011; Sun *et al.,* 2015). In Hong et al. (2017), the minor head-loss coefficient for valves was substituted with valve openness.

Pump characteristic curve equation was used in previous PSMs to predict the performance of pumps at different operating points. This relation was modelled in previous PSMs for fixed speed pumps (FSPs) using quadratic polynomial (Ulanicki *et al.,* 2007; Verleye and Aghezzaf 2013; Menke *et al.,* 2016c; Bonvin et al., 2017), piecewise linearisation (Wang and Brdys 2006; Giacomello et al. 2012; Menke *et al.,* 2016c), or constant (Menke *et al.,* 2016c; Price and Ostfeld 2015; Price and Ostfeld 2016) assuming pumps are running at their best efficiency points. Characteristic curve of variable speed pumps (VSPs) was modeled in previous PSMs using quadratic relation (Wang and Brdys 2006; Burgschweiger et al. 2008; Burgschweiger et al. 2009; Sun et al., 2015; Verleye and Aghezzaf 2016) or piecewise linear relation (Menke et al., 2016a).

To reduce number of decision variables and computational time, characteristic curves for pumps connected in parallel (usually exist in a pumping station) were combined into single characteristic curve using superposition principle (Hong et al., 2017).

Few PSMs didn't consider pump characteristic curve equation in the optimisation method (Price and Ostfeld 2013b; Schwartz *et al.* 2016). It was assumed that an operating point for a pump can be achieved by throttling the pump discharge valve or by varying the pump speed (Morton 1975).

Pump efficiency is an important parameter for pump energy cost calculation. This is because operating a pump during low electricity tariff at low efficiency might cost more than operating a pump during high electricity tariff at high efficiency (Skworcow et al., 2014). Many PSMs considered pump efficiency as constant for sake of simplicity (Coulbeck and Chen 1991; Ostfeld and Salomons 2004a; Price and Ostfeld 2015; Price and Ostfeld 2016). In Verleye and Aghezzaf (2013), pump efficiency was modelled as quadratic function of pump flow. Burgschweiger et al. (2008) and Burgschweiger et al. (2009) approximated the relation between pump flow and efficiency and used it to solve PSP. Approximation of pump efficiency gives inaccurate pump energy cost which might results in suboptimal solution. Other PSMs considered pump efficiency as a variable that changes with pump flow and variable (López-Ibáñez *et al.,* 2008; Giacomello *et al.,* 2012; De Paola et al., 2016). For more accurate calculations of pump energy cost, the efficiency of the motor, the variable speed drive, the coupling, and the cables (wire-to-water efficiency) should be considered (Moreno *et al.,* 2007).

For VSPs, it is important to note that pump efficiency curve shifts to the right with increase in pump speed. Not accounting for change in pump efficiency with change in its speed might reduce optimality of PSM solution as in Soonthornnapha (2017).

Pump brake power equation was approximated in several ways. In Giacomello *et al.* (2012), Verleye and Aghezzaf (2013), and Bonvin et al. (2017) pump brake power was modeled as linear function of flow. Piecewise linearization was used in Wang and Brdys (2006) to linearise pump brake power equation. In Menke *et al.* (2016c), pump brake power was modelled as quadratic function of flow. In Pelletier (1995), energy consumption factor for different pump combinations was used. These approximations will certainly cause inaccuracy in optimisation results.

In Zessler and Shamir (1989); Zhong and Lansey (1991); Jowitt and Germanopoulos (1992); Dandy and Crawley (1992); Crawley and Dandy (1993); Lansey and Awumah (1994); and Pasha and Lansey (2009); Zhuan et al. (2016), EPS was used offline (i.e. pre-optimisation) to fit a convex piecewise linear function that relates pump station energy consumption and flow for different pump combinations, demand patterns, and tanks' levels. Network hydraulics are embedded in this relation. This type of relaxation transfers PSP to a linear convex optimisation problem that can be easily solved. A similar non-linear relation is created in Tischer et al. (2003). However, aside from approximations made, these curves were generated offline in time consuming process because the network needs to be simulated for different spatial demands, different pump combinations, and different tanks' levels. Additionally, it is difficult to generate these curves for complex networks with multiple tanks and pumping stations. In addition, optimum pump station flow (continuous) needs to be converted to pump schedule (discrete) post optimisation. Thus, optimality and feasibility of the solution are not assured.

Leakages in some PSP were modelled using the function that models emitters (Rossman 2000) in which leakages are dependent on pressure. This function was linearised in Wang and Brdys (2006) PSM using piecewise linearisation. In

Skworcow et al. (2014), leakages were considered as constant and added to mass balance equation at connection nodes.

Tanks were modeled using a linear mass balance equation and in most PSMs water levels inside tanks were assumed constant during time steps (Ulanicki et al., 2007; Verleye and Aghezzaf 2013). In Little and McCrodden (1989), Jowitt and Germanopoulos (1992), Price and Ostfeld (2016) the effect of tanks' water levels on the network hydraulics was ignored. This might result in inaccurate calculations especially if tanks have high height and longtime steps are used (McCormick and Powell 2004).

Tanks in previous PSMs were assumed to have single inlet/outlet pipe. However, in some WDSs tanks have inlet pipe at the top and another outlet pipe at the bottom. This type of tanks were modelled in Kurian et al. (2018) PSM.

The topology of the water network, whether if it is star structure, tree structure, cascade structure, or mesh structure (Cembrano et al., 2000), affect the convergence of the PSM. For example, a change in a pump operation in a mesh structure WDS has effects on most of the network. However, a change in a pump operation in a tree structure WDS has effects on a limited area of the network. Thus, the performance of a PSM should be tested on different WDSs with different topologies.

Spatial decomposition of WDSs was used to simplify PSP. It works fine when the topology of the WDS is of star, tree, or cascade type (Coulbeck 1977; Brdys 1992; Pelletier 1995). However, it is difficult to apply spatial decomposition on mesh type WDS because the hydraulic elements are highly interconnected and flows' directions are not fixed (Cembrano et al., 2000).

Water quality model for a WDS relies on its hydraulic model, conservation of mass for constituents, and reaction kinetics. Water quality modelling includes equations that represent mixing at nodes, mixing at tanks, bulk flow reactions, and pipe wall reactions (Rossman 2000). Most PSM assumed complete mixing at nodes and tanks (Mehrez *et al.,* 1992; Cohen et al., 2003; Price and Ostfeld 2016), and first order bulk/wall reactions for chlorine (Boccelli et al., 1998; Munavalli and Kumar 2003).

Hydraulic and water quality equations are solved at discrete time intervals using different algorithms such as gradient algorithm (Todini and Pilati 1987) for the hydraulic model and Lagrangian time-based approach (Liou and Kroon 1987) for the water quality model. These time intervals are called hydraulic time step and water quality time step. The length of these time steps has effect on computational time, optimality and feasibility of the solution in PSM. The length of the hydraulic time step is usually 1 hour while the length of the water quality time step is usually 5 minutes. These time steps are different than time steps of the pump schedule (see subsection 2.2.2).

*EPANET 2.0* is the most famous hydraulic simulation toolkit for solving PSP. This is because it is an open source software. Additionally, it can be easily linked to an optimisation program to retrieve hydraulic variables and modify network characteristics. However, *EPANET* toolkit has some limitations that were overcome to enhance its application for solving PSP. In Marchi and Simpson (2013), the *EPANET* toolkit was modified to make VSPs efficiency change with speed to get correct computation of VSPs energy consumption. In Marchi et al. (2016), the *EPANET* toolkit was modified to allow for direct change of rule-based control statements from the optimisation algorithm. In Shang et al. (2008), *EPANET* toolkit was improved to enable modelling of multiple constitutes. Price and Ostfeld (2016a) enabled *EPANET* toolkit to reinitialise the simulation directly to the wanted time step instead of the initial time step. Lopez-Ibanez et al. (2012) developed a thread-safe variant of *EPANET* that supports parallel computing for pump scheduling. The previous modifications make *EPANET* toolkit more accurate, flexible, and efficient. Uber et al. (2018) encouraged researchers to move on and solve other limitations in *EPANET* toolkit to make it more powerful for solving PSP.

## 2.3 Pump Scheduling Optimisation Modelling

As mentioned in chapter 1, PSP is a complex problem that is non-linear, mixed integer, and non-convex. Thus, there is no unique approach to model and solve this problem. Instead, the problem was formulated in many different ways based on the objectives and the optimisation method that will be used to solve the problem. In general, any optimisation model has three main components, which are objectives, decision variables, and constraints. These three components and how they were represented in the previous PSMs will be discussed in the following subsections.

### 2.3.1 Objectives

The objectives in previous PSMs were to optimise electrical energy cost, water cost, water quality, leakage, tank storage, and number of pump switches.

The great majority of PSMs available in literature had objective of reducing electrical energy cost. There are two types of electrical energy cost: energy charge and maximum demand charge. Energy consumption charge (also called unit charge or time of use charge) depends on the total electrical energy consumed during a billing period. Maximum demand charge depends on the peak power consumed during a billing period. Energy charge is billed in £/kWh basis while demand charge is billed in £/kW basis. Both energy and maximum demand charges might change from one hour to another or from one season to another.

Minimizing both energy consumption and maximum demand charges is difficult due to the trade-off between them. Most PSMs considered minmizing energy charge only for sake of simplicity, althoug maximum demand charge can have significant effect. Minimizing both energy and maximum demand charges was successfully attained using different optimisation methods such as linear programming in Jowitt and Germanopoulos (1992) and Little and McCrodden (1989), genetic algorithms in Rao and O’Connell (2002), dynamic programming in McCormick and Powell (2003b), Nitivattananon (1994), Chou *et al.,* (1988), and Sterling and Coulbeck (1975a), six different multi-objective evolutionary algorithms in Barán *et al.,* (2005), simulated annealing in Sousa et al. (2006) and McCormick and Powell (2004), ant colony optimisation in López-Ibáñez *et al.,* (2008), multi-objective harmony search algorithm in Kougias and Theodossiou (2012), multiobjective NSGA II in Makaremi et al. (2017).

Ahcene and Saadia (2018) demonstrated that reducing energy cost does not necessarily reduce energy consumption and vice versa. This is because sometimes a PSM enforces many pumps to run during low electricity tariff, which will reduce energy cost but might increase energy consumption during the whole optimisation time horizon.

When electricity tariff is constant then reducing energy consumption will certainly reduce electricity cost. In this case, the objective of pump scheduling could be to minimise the specific energy consumption (kWh/m$^3$) (Bene and Hos 2012). Usually, big pumps in WDSs have lower specific energy cost than small pumps. A good pump schedule in this case will enforce big pump to start and store excessive water in tanks during low demands.

WDSs are usually supplied from different water sources that have different water costs. It is wise to consider minimising water cost in addition to electrical energy cost. This is because running a pump at high electrical tariff to draw water from cheap water source can have less total cost than running a pump at low electrical tariff to draw water from expensive water source. Both electrical energy cost and water cost have the same unit of measurement. So they can be added in a single objective function without using weighting factors. Water cost was minimised in previous PSMs using linear programming in Price and Ostfeld (2013a), Ulanicki and Orr (1991), and McCormick and Powell (2003a), non-linear programming in Verleye and Aghezzaf (2016), Ostfeld and Shamir (1993a), Ostfeld and Shamir (1993b), Brdys et al. (1995), Cembrano et al., (2000), Cohen *et al.,* (2000a), Cohen *et al.,* (2000b), Cohen *et al.,* (2000c), Burgschweiger et al. (2008), Burgschweiger et al. (2009), Cohen et al. (2009), and AbdelMeguid (2011), genetic algorithms in Ostfeld and Salomons (2004), and Ostfeld et al. (2011).

Minimising energy cost by filling tanks during low electrical tariff and emptying them during high electrical tariff usually deteriorates chlorine and water age in WDSs. This is because the duration of filling or emptying is usually long (e.g. 8 hours) depending on the electrical tariff structure, the demand patterns, and tanks' sizes. Many authors confirmed the trade-off between minimising energy cost and optimising water quality in WDSs (Sakarya and Mays 2000; Ostfeld and Salomons 2006; Arai et al. 2013; Kurek and Ostfeld 2014; Mala-Jetmarova et al. 2014). A good pump scheduling method should not overlook water quality. This is because WDSs usually have different sources that have different water qualities. Additionally, the different pump schedules make different paths for water from sources to consumers. Long paths for water reduce chlorine and increase water age. Non conservative water quality parameters such as total organic carbon, water age, and chlorine were optimised using linear programming in Brdys *et al.,* (1995), genetic algorithms in Kurek and Brdys (2007), Murphy et al. (2007), Gibbs et al. (2010a,b), and Dandy and Gibbs (2003), model predictive control in Biscos *et al.,* (2002, 2004), and Duzinkiewicz et al. (2005), evolutionary algorithm in Prasad and Walters (2006), linear programming in Arai *et al.,* (2012), strength pareto evolutionary algorithm II in Kurek and Ostfeld (2013, 2014). Conservative water quality parameters such as salinity were optimised in Dandy and Crawley (1992), Cohen et al. (2003), Mala-Jetmarova *et al.,* (2014).

Different treatment plants have different treatment methods and costs. Water quality in WDSs was optimised in three different approaches. The first approach is to minimise chemicals mass/cost in boosters/treatment plants subjected to the minimum/maximum required concentrations at demand nodes (Pool and Lansey 1997; Boccelli et al., 1998; Tryby et al. 2002; Prasad et al., 2004; Ostfeld and Salomons 2006; Gibbs et al., 2010a; Fanlin et al., 2013). Treatment cost can be added to energy cost in one single objective function. The second approach is to minimise the deviation between actual and desired concentrations at demand nodes (Sakarya and Mays 1999; Sakarya and Mays 2000; Biscos et al. 2002, 2004; Sakarya and Mays 2003; Munavalli and Kumar 2003; Propato and Uber 2004; Goldman et al., 2004; Kang and Lansey 2010). The third approach is to minimising the number of instances of not achieving the minimum required water quality (Ewald et al., 2008; Kurek and Brdys 2006). Choosing the best approach depends on the water utility preferences. For example, if water quality is a top priority, then it is preferred to go with minimising the difference between actual and desired concentrations (the second approach). Additionally, the capabilities of the optimisation method in hands and the required computation efficiency might enforce the decision maker to choose certain approach.

Electrical tariff is usually low during night. Thus, PSMs that are driven by minimisation of energy consumption charges only enforce pumps to start during night. However, starting pumps during night increases pressure and leakages in the network because water demand is also low during that time. Minimising energy cost and pressure/leakages are conflicting objectives. Thus, Wang and Brdys (2006), Giustolisi et al., (2012), Tahavori et al. (2013), and Hashemi et al. (2013b) considered minimising leakages as additional objective to energy consumption cost.

To ensure that tanks balance well during the optimisation time horizon, the majority of previous PSMs use constraint to enforce tanks' final water level to be at least equal to tanks' initial water level. However, some PSMs considered minimising the difference between tanks' initial and final water level as an objective in addition to energy cost (Dandy and Crawley 1992; Crawley and Dandy 1993; McCormick and Powell 2003a; Van Zyl *et al.,* 2004; Barán *et al.,* 2005; Fiorelli *et al.,* 2013). In this way, tanks' water levels are allowed to drop at the fever of extra reduction in energy cost. In Carrijo et al. (2004), maximising water level in tanks was considered as another objective in addition to minimising energy cost.

Optimum pump schedules usually have high number of pump switches. High number of pump switches increases tears and wears in pumps and increases maintenance cost. Additionally, high number of pump switches can cause motor overheating, water hammer, high turbidity, stress on deep well mechanical equipment (Housh and Salomons 2019). Thus, many PSMs considered minimising number of pump switches as an objective in addition to energy cost (Savic *et al.,* 1997; Barán *et al.,* 2005; Lopez-Ibanez et al., 2005; Al-Ani and Habibi 2012; Bene et al., 2013; De Paola *et al.,* 2016; Makaremi et al., 2017; Housh and Salomons 2019). However, minimizing number of pump switches is not sufficient for pump health. Having 2 pump switches with short time gap between them might be more harmful than having 3 pump switches with long time gap between them. Thus, in Housh and Salomons (2019) maximizing the switch time gap was considered as an objective.

Other objectives that were considered in previous PSMs are reducing greenhouse gas (Stokes et al., 2015a; Stokes et al., 2015b; Blinco et al., 2016), increasing operational reliability (Odan et al., 2015), minimising difference between actual and required pressure at demand nodes (Carrijo et al., 2004; Ostfeld and Tubaltzev 2008), minimising excessive pressure (Wang and Brdys 2006), minimising crop yield reduction due to poor water quality (Cohen et al., 2003), reducing water resources depletion (Wang et al. 2009), meeting the required water demand (Carrijo et al., 2004).

Many PSMs treated the previously mentioned objectives (demand charge, water quality, leakage, tank storage, pump switches) as constraints. These constraints will be discussed in section 2.3.3. The addition of penalties in the objective function (for constraint violation) will be also discussed in section 2.3.3.

## 2.3.2 Decision Variables

This subsection discusses the different decision variables that were used in previous PSMs.

PSP is supposed to be solved for finite upcoming time horizon. The length of pump scheduling time horizon depends on the demand pattern and electrical tariff structure. If they repeat every day, then 1 day scheduling time horizon will be enough. If they repeat every week, then the scheduling time horizon should be 1 week for more optimistic results. The majority of previous PSMs has 1 day pump scheduling time horizon.

As mentioned in chapter 1, PSP is a discrete optimisation problem. Having continuous time horizon for pump scheduling requires infinite number of decision variables and exhaustive computational efforts. Additionally, there might be more than one optimum schedule that give equal objective value. Thus, most previous PSMs sliced the time horizon into time steps. During each time step, decision variables (e.g. pumps' statuses), state variables (e.g. pumps flow, tanks' levels), and disturbance variables (e.g. demands) are considered constant. There are two main drawbacks for discretising the pump scheduling time horizon. First, it might result in suboptimal solution, because pumps should have freedom to switch on or off at any time to get an optimistic solution.

Additionally, pump should be able to stop/start more than once during a time step. The optimality of the solution in the case of sliced time horizon might be increased by reducing the length of the time steps but at the expense of computation time. The second drawback is that having fixed state variables during each time step might result in infeasible solution, because state variables (demand, pump flow, tank level) in real WDSs are dynamic and might change at any time. In Bagirov et al. (2013), the pump scheduling time horizon was not discretized into time steps. Instead, pumps' run times were considered as continuous decision variable (FSPs can start and stop any time during the pump scheduling time horizon). However, the method can not be used if there is more than two electrical tariffs during the scheduling time horizon.

While majority of PSMs choses length of time step to be 1 hour, few methods have time step length of 15 minutes (Naoum-Sawaya *et al.* 2015). Jowitt and Germanopoulos (1992) and Wang et al. (2009) suggested to choose the length of time step based on the structure of electrical tariff and times at which water in tanks can be expected to reach maximum or minimum limits. This is to reduce number of time steps and increase computational efficiency.

There is another different approach to optimise the operation of pumps known as rule based control. In this approach, instead of optimising the status of each pump for the upcoming time steps, pumps switch on/off based on optimistic rules (Tischer et al., 2003; Georgescu and Georgescu 2010; Alvisi and Franchini 2016; Marchi et al., 2016; Marchi et al., 2017). The optimistic rules can be water level in downstream tanks or pressure in downstream nodes. However, it had been noticed that feedback rules gave higher energy cost than scheduling the operation of pump ahead of a time (AbdelMeguid and Ulanicki 2011; Blinco et al., 2016). This is because in rule based control, instead of directly optimising pumps' statuses, we optimise the state variables which trigger pumps' operation.

Decision variables are determined based on the objectives of pump scheduling and the optimisation method that will be used to solve the PSP (e.g. linear programming can not be used to optimize non-linear objective function).

For minimising electrical energy cost, decision variables can be the status of FSPs, the speed of VSPs, and valves' settings. The status of a FSP during each time step was represented in previous PSMs in three different ways (Ormsbee *et. al.,* 2009):

1- FSP is either on or off during the whole time step (Mackle et. al., 1995; Savic and Walters 1997; Goldman and Mays 1999; Boulos et al., 2001; McCormick and Powell 2004; Baran et al., 2005; Rao and Salomons 2007; Salomons et al. 2007; Martínez et al. 2007; Shamir and Salomons 2008; Giacomello et al. 2012; Ibarra and Arnal 2014; Kang 2014). In this case, FSP status was presented as binary variable, where zero means pump is off and one means pump is on. In some methods like Ulanicki et al. (2007) and Skworcow et al. (2014), number of running pumps during in a time step was considered as continuous variable (e.g. optimum number of running pumps during a time step can be 1.5) then a method to transfer that into discrete values was used.
2- FSP can start at the beginning of time step and stop any time during the time step (Chase and Ormsbee 1989; Chase 1990; Brion and Mays 1991; Cembrano et al., 2000). This decision variable gives more optimistic solution than the previous one. The FSP status was presented as non-integer variable of time fraction bounded by zero and one.
3- The number of time steps is predefined based on the maximum allowed number of pump switches (Sakarya and Mays 2000; McCormick and Powell 2004; López-Ibáñez et al., 2005; López-Ibáñez et al., 2008; Prasad et al., 2012). The length of each time step, during which a FSP was either on or off, was an integer variable to be determined by the optimisation method. This is called time-controlled triggers and it is recommended for reducing the number of decision variables and computational time.

VSPs are known for reducing energy consumption and leakage since they provide better control (Wood and Lingireddy 1995; Lingireddy and Wood 1998; Hashemi et al., 2013a; Hashemi et al., 2013b). Many pump scheduling methods including recent ones overlook VSP for sake of simplicity (Singh and Kekatos 2018) or because many WDSs have FSPs only. Previous PSMs which optimize operation of VSPs considered speed during each time step as discrete decision variable (Chen and Coulbeck 1991; Jowitt and Germanopoulos 1992; Ormsbee and Lansey 1994; Pezeshk and Helweg 1996; McCormick and Powell 2004; Sousa et al. 2006; Moreira and Ramos 2013; Abkenar et al., 2015; Hong et al., 2017) or as continuous decision variable (Ulanicki and Orr 1991; Wegley et al., 2000; AbdelMeguid 2011; Price and Ostfeld 2012b; Hashemi et al., 2013a; Hashemi et al., 2013b; Sun et al., 2015; Verleye and Aghezzaf 2016, Gong and Cheng 2018). In Bagloee *et al.,* (2018), it is initially assumed that VSPs can have certain discrete speed values, then curve fitting method was used to enable VSPs to have any continuous value. Considering pump speed as continuous variable increases the optimality of the solution, but that depends on the capabilities of the optimisation method.

The operation of valves in WDSs effects the previously mentioned objectives of pump scheduling. For example, rerouting water flows effects the quality of water at demand nodes (Prasad and Walters, 2006; Alfonso et al., 2010). Valves' controls in previous PSMs were represented using binary variables (i.e. valves are fully opened or closed) (Biscos et al., 2002; Biscos et al., 2003; Carrijo et al., 2004; Prasad and Walters 2006; Jamieson et al., 2007; Alfonso et al., 2010; Giustolisi et al., 2012), discrete valves' positions (Ulanicki and Kennedy 1994; Cembrano et al., 2000; Cohen et al., 2000b; Cohen et al., 2000c; Ostfeld and Salomons 2004a; Ostfeld and Salomons 2006; Rao et al., 2007; Rao and Salomons 2007; Martinez et al., 2007; Kang and Lansey 2009, 2010), continuous valves' positions (Biscos et al., 2002, 2003; Ulanicki and Orr, 1991; Ulanicki et al., 2007), or valves' flows (Carpentier and Cohen 1993; Jowitt and Germanopoulos 1992; Skworcow et al., 2014; Sun *et al.,* 2015; Bonvin et al., 2017; Bagloee *et al.,* 2018), valves' headlosses (Cohen et al., 2000b, 2009; Kelner and Leonard, 2003), settings for pressure reducing valves (Murphy et al., 2007; Salomons et al., 2007; Shamir and Salomons 2008; Skworcow et al. 2014), valve flow direction (Gleixner et al., 2012; Singh and Kekatos 2018). Decision variable for valves is usually chosen based on optimisation objectives, valve types, optimisation method, and required optimality of the solution.

If the objective of pump scheduling is to minimise water cost, then the decision variable can be the flow of pumps which draw water from sources (Cohen et al., 2003; AbdelMeguid 2011; Bonvin et al., 2017), treatment plant removal ratio

(Cohen et al. 2003; Ostfeld and Salomons 2004a; Ostfeld and Salomons 2004b; Cohen et al., 2009), solute concentration (Mehrez *et al.,* 1992).

For minimising water leakage in WDSs, the decision variable can be valves settings (Vairavamoorthy and Lumbers 1998, Skworcow et al., 2014) and pumps status (Price and Ostfeld 2013b; Price and Ostfeld 2014b).

Chlorine booster pumps can be scheduled (simultaneously with water pumps) to optimise water quality in WDSs. The decision variable for booster chlorine pumps is usually the chlorine mass injection flow rate (Dandy and Gibbs 2003; Munavalli and Kumar 2003; Ostfeld and Salomons 2006; Gibbs and Dandy 2010).

Due to its complexity, many PSMs solve PSP implicitly by optimising one or more of the state variables then creating pump schedule which follows that optimum state variables. State variables which were treated as decision variables are tanks' levels (Ormsbee *et al.,* 1989; Jowitt and Germanopoulos 1992; Atkinson *et al.,* 2000; Van Zyl *et al.,* 2004; Broad et al., 2010), pump station head (Zhong and Lansey 1991; Price and Ostfeld 2012b; Price and Ostfeld 2013b; Price and Ostfeld 2014b; Gong and Cheng 2018), pump station flow (Zessler and Shamir 1989; Jowitt and Germanopoulos 1992; Nitivattananon et al., 1996; Pasha and Lansey 2009; Arai *et al.,* 2012; Giacomello et al. 2012; Bene et al., 2013; Singh and Kekatos 2018), head at nodes (Giacomello et al. 2012; Ghaddar *et al.,* 2015), flow in pipes (Giacomello et al. 2012; Price and Ostfeld 2012b; Price and Ostfeld 2013b, Price and Ostfeld 2014b; Ghaddar *et al.,* 2015). Solving PSP indirectly can increase number of pumps' switches and reduce system stability because pumps follow triggers without knowing their future dynamics. Additionally, pumps might not be able to attain the optimum triggers or the optimum triggers might be attained by different pump combinations that have different energy consumptions. Thus, solving PSP indirectly might result in suboptimal or infeasible solution.

### 2.3.3 Constraints

There are two types of constraints in PSP; hydraulic constraints and operational constraints. Hydraulic constraints represent the conservation of mass (in nodes and tanks) and energy (in pipes, pumps, and valves). Hydraulic constraints are essential to fulfill the natural behavior of the water network and they are discussed in section 2.2. Operational constraints are optional; they depend on decision maker requirements such as number of pump switches. Decision maker constraints have impact on the efficiency and effectiveness of PSP (Clarkin et al., 2018). For example, increasing number of constraints will reduce computational efficiency of mixed integer optimisation methods. In this subsection, the different operational constraints in previous PSMs will be discussed.

High water flow rates (speed of more than 2 m/s) put pipes in high risk of burst especially during surge. Thus, several PSMs limits flow in water pipes (Cohen 2003; Verleye and Aghezzaf 2013; Ghaddar *et al.,* 2015; Verleye and Aghezzaf 2016; Bagloee *et al.,* 2018).

The minimum required pressure constraint at demand nodes is necessary to guarantee the quality of service for consumers, while maximum pressure constraint is necessary to reduce leakages (López-Ibáñez *et al.,* 2008; Price and Ostfeld 2012b; Giacomello *et al.,* 2012; Price and Ostfeld 2014b; Costa et al., 2015; Price and Ostfeld 2015; Odan *et al.,* 2015; Price and Ostfeld 2016; Verleye and Aghezzaf 2016; Bagloee *et al.,* 2018). In Pezeshk and Helweg (1996) and in Abkenar et al. (2015), few critical nodes were selected so that if they satisfied minimum/maximum pressure constraint, it would be satisfied elsewhere in the network. A pressure dependent water leakage constraint was used in AbdelMeguid (2011), Price and Ostfeld (2013b), Price and Ostfeld (2014b).

Tanks in WDSs have several advantages. They play major role in reducing energy cost by storing water during low electric tariff and releasing water during high electric tariff. Additionally, they support demand variations, allow for smooth operation of pumps, increase water security, and break pressure in the network. However, tanks might deteriorate water quality and enforce pumps to run against high static head when water levels' in tanks are high. Thus, minimum and maximum tanks' water level constraint should be carefully specified. This constraint was used in Price and Ostfeld (2016) to improve chlorine in the network by reducing tanks' maximum water level. Most previous PSMs enforce tanks level at the end of optimisation horizon to be at least equal to or greater than initial level (López-Ibáñez *et al.,* 2008; Giacomello *et al.,* 2012). Some other PSMs allow for certain deficit between initial and final combined water volume in all tanks (Bagirov et al., 2013; Makaremi et al., 2017), in favor of lower energy consumption. The deficit can be compensated during weekend low water demands.

If there is a group of parallel pumps in a pumping station and they are identical (i.e. they have the same pump characteristic curve) then it does not matter (from optimisation point of view) which pump is on and which is off during a time step. What matters is the number of pumps running in each time step. Here are three ways to take advantage of this feature. In Bene et al., (2010); Gleixner, et al. (2012); Menke, et al. (2016c); and Bonvin, et al. (2017) a constraint that specifies the order of switching for parallel identical pumps was used. This is to reduce the number of possible solution and computation time. Another way of doing this is to have an integer decision variable for the number of running pumps in a time step, instead of having a binary decision variable for each pump for each time step (Bonvin, et al., 2017). In this regard, the number of possible solutions and the computational time are reduced. Operators can then choose which pumps to start based on their preferences (e.g. to start pumps that have lowest running hours). In Menke et al. (2016c) composite pump curves are created for pumps in a pumping station and only one curve can be triggered during a time step.

Optimum pump schedules usually have high number of pump switches, which depend on electrical tariff structure, demand patterns, pumps' sizes, and tanks' sizes. High number of pump switches might increase maintenance cost due to tears and wears. Thus, many PSMs constrained number of pump switches (Lansey and Awumah 1994; Savic *et al.,* 1997; Boulos et al., 2001; Van Zyl et al., 2004; López-Ibáñez *et al.,* 2008; Selek et al., 2012; Price and Ostfeld 2015; Costa et al., 2015; Price and Ostfeld 2016; De Paola *et al.,* 2016; Menke *et al.,* 2016b). Some optimisation methods cannot handle this constraint (Jowitt and

Germanopoulos 1992; Ostfeld and Salomons 2004a; Hashemi et al., 2013b). In this case, operators were given the choice to reduce pump switches heuristically. To avoid successive switches, Burgschweiger et al. (2009) suggested another similar constraint which is to specify minimum time during which a pump is on or off. However, this constraint might not be practical in case if we have big pumps that supplies small demand nodes and tanks. In this case we might need to start/stop pumps for short durations.

Due to uncertainties in WDSs (e.g. demands, pumps' curves, pipe diameters, pipe friction…etc), PSM should re-run frequently to ensure that computed state variables (e.g. tanks' levels) matches with that in the field. However, re-running the PSM might cause violation of maximum number of pump switches, because the PSM is unaware of previous switches. This problem was solved in Baran et al. (2005), Odan et al. (2015), Abdul Gaffor (2017) by combining previously implemented pump schedule and current optimised pump schedule.

Water demand in PSMs is considered as a disturbance variable that cannot be controlled and has effect on objective function and state variables (Schwartz *et al.* 2016). For real-time control, it is important to couple PSM with short-term demand forecasting method (Moss 1979; McCormick and Powell 2003b; Salomons *et al.,* 2007; Kim *et al.,* 2007; Burgschweiger et al., 2008; Burgschweiger et al., 2009; Kang *et al.,* 2015; Odan et al., 2015; Thouheed 2017; Abdul Gaffoor 2017). In Goryashko and Nemirovski (2014) water demand that caused the highest energy cost was used in a robust counter part methodology to cater for demand uncertainty level of 20%. In Khatavkar and Mays (2017), demand was modeled using chance constraint, which assumes that demand variation is normally distributed.

Another factors that might affect maintenance cost and were considered in previous PSMs are the accumulative operating time of pumps (Tang *et al.,* 2014), pump vibration (Luo et al. 2012) and pump cavitation (Torregrossa and Capitanescu 2019). The reliability of the previously mentioned metrics for maintenance cost needs to be investigated. Additionally, researchers are encouraged to look for other operational expressions such as pump efficiency to quantify maintenance cost.

Conservative water quality parameters were constrained in Mehrez *et al.,* (1992), Ostfeld and Shamir (1993a), Ostfeld and Shamir (1993b), Percia *et al.,* (1997), Cohen *et al.* (2000a), Cohen *et al.* (2000c), Cohen et al. 2003, Ostfeld and Salomons (2004b), Propato and Uber (2004). Non-conservative water quality parameters were constrained in Ostfeld and Shamir (1993b), Goldman (1998), Goldman and Mays (2012), Sakarya and Mays (1999), Sakarya and Mays (2000), Sakarya and Mays (2003), Ostfeld and Salomons (2006), Brdys et al. (2013), Kurek and Ostfeld (2013).

Water treatment plants have several limitations that were incorporated in previous PSMs such as treatment capacity (Chen and Coulbeck 1991; Jowitt and Germanopoulos 1992; AbdelMeguid, 2011), extraction limits to reduce depletion in water sources (Ostfeld and Salomons 2004a; Verleye and Aghezzaf 2013; Torregrossa and Capitanescu 2019), allowed fluctuation in extraction (AbdelMeguid 2011; Verleye and Aghezzaf 2016), maximum removal ratios (Ostfeld and Shamir 1993a; Ostfeld and Shamir 1993b; Cohen *et al.,* 2000a; Cohen *et al.,* 2000c; Cohen et al., 2003; Ostfeld and Salomons 2004a; Ostfeld and Salomons 2004b; Cohen et al., 2009).

Maximum demand charge was considered as a constraint (not as an objective, see section 2.3.1) in Gibbs et al. (2010a). Warning codes generated by hydraulic simulators due infeasible hydraulic conditions (e.g. pump cannot supply sufficient pressure) were also constrained (López-Ibáñez et al., 2008; Kurek and Ostfeld 2013).

The previous constraints were handled in literature in two ways: as hard constraints or as soft constraints. Hard constraints are inequalities that must be satisfied. Soft constraints are given some tolerance by penalizing them in the objective function (Mackle *et. al.,* 1995). Penalties in the objective function were used to handle different constraints such as pump switches (Cembrano et al., 2000; Van Zyl *et al.,* 2004; Menke *et al.,* 2016b; Hong et al., 2017), warning codes in hydraulic simulators (De Paola et al., 2016; Singh and Kekatos 2018), tank limits (Kougias and Theodossiou 2012), chlorine (Kurek and Ostfeld 2013), water age (Murphy et al., 2007), pressure at demand nodes (De Wrachien et al., 2017).

Penalising constraints violation in the objective function might lead to infeasible or suboptimal solution. If violation value for a constraint (e.g. pressure at demand nodes) is too small compared to main objective values (e.g. energy cost), then the optimisation method will focus more on minimizing energy cost and constraint might be violated. On the other hand, if violation value for pressure at demand node is too big compared to energy cost, then the optimisation method will focus more on pressure violation at demand node and energy cost might be suboptimal. Thus, careful coefficients for penalty approach should be chosen, which is a time expensive experimental process (Bene et al., 2010). López-Ibáñez *et al.* (2008) and Abdul Gaffoor (2017) suggested to rank solutions based on number of violations and importance of constraints instead of penalising the violation of constraints in the objective function.

The previous operational constraints such as demand charge, water quality, leakage, tank storage, and pump switches can be treated as objective as mentioned in subsection 2.3.1. Deciding whether to treat a parameter as objective or constraint depends largely on decision maker preferences. Solving PSP as a multi-objective optimisation problem allow the decision maker to investigate the tradeoff between the different objectives. However, it is a time consuming process that requires a selection procedure and in many cases multi-objective optimisation gives Pareto inefficient solutions. On the other hand, having single objective function and adding many operational constraints will tighten the problem, reduces the number of possible solutions and computation time. However, the optimality of the solution might reduce due to the limited choices of solutions.

## 2.4 Pump Scheduling Optimisation Methods

In computational complexity theory, problems which are difficult to solve in polynomial time (time required by a computer to solve the problem) are called non-deterministic polynomial time (NP) hard problems (Yate et al., 1984). In NP-hard problems, polynomial time increases exponentially with problem size. Most real-world scheduling problems are NP-hard for which time efficient global optimum algorithms do not exist (Tompkins 2003; Talbi 2009). Pump scheduling problem is proven to be an NP-hard problem as mentioned in Chapter 1.

Optimisation methods which were used to solve PSP can be classified into two main categories: mathematical optimisation methods and heuristic optimisation methods. Mathematical optimisation methods follow a set of instructions and a sequence of programs to solve the optimisation problem whereas heuristic optimisation methods search in a state space based on insights, experienced choices, and educated guesses to find the optimal solution. Mathematical optimisation methods are deterministic methods, i.e. they always perform the same way and give the same answer for the same initial conditions, while heuristic optimisation methods are stochastic methods, i.e. they give different solution for each execution.

Pump scheduling is a nonconvex problem that has nonlinear equations and mixed integer decision variables. Thus, using mathematical optimisation methods to solve the problem is difficult without relaxations and loss of accuracy. On the other hand, using heuristic optimisation methods to solve the problem is time consuming due to the huge number of possible solutions. Thus, none of the above two main categories is perfect for solving PSP due to the tradeoff between optimality and computational efficiency. The adage that says "There is no such thing as a free lunch" applies to the selection of optimisation method to solve PSP. An optimisation method that performs well in a certain criteria (e.g. computational time) fails in another criteria (e.g. optimality of the solution). In fact, there is no consensus on the best optimization method that can solve PSP. Instead, modeling of PSP had been adapted in different ways as shown in sections 2.2 and 2.3 to fit in the different optimisation methods. The choice of the most suitable optimisation method to solve PSP depends largely on decision maker preferences.

Hybrid optimisation methods that include both mathematical and heuristic optimisation methods exist in literature. Additionally, multi-objective optimisation methods were used to simultaneously optimise the different objectives of PSP.

Sensitivity analyses were made to proof the robustness of previous PSMs (Skworcow et al., 2014). This includes changing demands (Marchi et al., 2016), changing initial water level in tanks (Savic et al., 1997), changing in water quality limits (Cohen et al., 2004; Cohen et al., 2009), changing water cost, changing a demand node to a source node, changing demand node elevation, excluding valves from network (Ostfeld and Salomons 2004a), adding new chlorine station (Ostfeld and Salomons 2006).

The mathematical optimisation methods and the heuristic optimisation methods will be discussed in the following subsections 2.4.1 and 2.4.2, respectively. Hybrid optimisation methods, multi-objective optimisation methods, and model predictive control will be discussed in subsection 2.4.3. Subsection 2.4.4 talks about existing computer software that were developed to solve PSP.

### 2.4.1 Mathematical Optimisation Methods

In this subsection, mathematical optimisation methods which were used to solve PSP will be explored. These methods are non-linear programming, quadratic programming, cone programming, dynamic programming, linear programming, stochastic programming, and graph theory.

Non-linear programming is the most general form for PSP. In non-linear programming, the objective function or one of the constraints are non-linear. In fact, other formulations of PSP can be considered as special cases of non-linear programming. Many researchers model PSP as a non-linear programming problem (Chase and Ormsbee 1989; Brion and Mays 1991; Ulanicki and Orr 1991). The shortfall in non-linear programming is that it can not handle large number of decision variables.

Generalized reduced gradient method is a well-known technique for solving nonlinear programming problems. It is an iterative technique that keeps changing the value of the decision variables until the gradient (i.e. slope) of the objective function becomes zero, which means that the technique has reached an optimum solution. It is a fast solving technique that had been used in several PSMs (Cembrano et al., 2000; Skworcow et al., 2014). However it can be easily trapped in local minimum solution and the final solution is highly dependent on the initial conditions. Additionally, the objective function should be smooth (i.e. no discontinuities) which is not applicable to PSP because some pump combinations might not give feasible solutions. In AbdelMeguid (2011) a heuristic method was used after generalized reduced gradient method to discretise pumps' statuses decision variables.

Mixed integer non-linear programming is a non-linear programming where at least one of the variables is required to be integer. Different approaches were used to solve PSP which was formulated as mixed integer non-linear programming, such as branch and bound algorithm (Gleixner *et al.,* 2012; Costa et al. 2015; Menke et al. 2016c), generalized decomposition algorithm (Verleye and Aghezzaf 2016), Lagrangian decomposition (Ghaddar *et al.,* 2015; Naoum-Sawaya et al., 2015) . Branch-and-bound usually suffers from exponential increase of computation time with number of pumps. When decomposition is used, the solution for the sub-problem might not be feasible or optimum for the original problem.

Quadratic programming is the best behaved formulation for non-linear programming problem, in which the objective function is non-linear and the constraints are linear. In Ulanicki et al., (2007), Menke et al. (2016c) and Bonvin et al. (2017), PSP was formulated and solved as mixed integer quadratic programming.

PSP was modelled as a second order cone programming optimization problem in Fooladivanda and Taylor (2015), Fooladivanda and Taylor (2017), and Singh and Kekatos (2018). In second order cone programming, the PSP need to be relaxed to a convex optimization problem. Thus, optimality of the solution is not assured.

Dynamic programming copes easily with the nonlinearity in PSP. However, Dynamic programming is impractical technique for optimisation problems that has large number of state variables such as PSP (Dreizin 1970; Murray and Yakowitz 1979; Joalland and Cohen 1980; Coulbeck and Orr 1983; Solanas and Montoliu 1988; Ormsbee et al., 1989; Kim et al., 2015). Thus, the use of dynamic programming to solve PSP is limited to small size WDSs. That limitation was overcome by using different decomposition and aggregation methods (Fallside and Perry 1975; Sterling and Coulbeck 1975a; Sterling and Coulbeck 1975b; Coulbeck 1977; Coulbeck and Sterling 1978; Coulbeck et al., 1987; Alla and Jarrige 1988; Carpentier 1983; Zessler and Shamir 1989;

Nitivattananon et al. 1996; Gong and Cheng 2018). However, decomposition and aggression can easily cause loss of accuracy and optimality.

Linear programming was used many times to solve PSP, because it takes seconds to find optimum pump schedule for large WDS (Nakahori *et al.,* 1978; Jowitt and Germanopoulos 1992; Dandy and Crawley 1992; Crawley and Dandy 1993; Pasha and Lansey 2009). However, linear programming requires the objective function and the constraints to be linear, which is not compatible with the nonlinear nature of PSP. Thus, optimality and feasibility is not ensured with linear programming.

Mixed integer linear programming is special case of LP where at least one of decision variables is required to be integer. Several authors formulated PSP as a mixed integer linear programming problem (McCormick and Powell 2003a; Verleye and Aghezzaf 2013). Different approaches were used to solve PSP which was formulated as mixed integer linear programming, such as branch and bound algorithm (Price and Ostfeld 2012b; Brdys & Ulanicki, 1994) and decomposition (Kurian et al. 2018; Bagloee *et al.,* 2018).

Since demand is usually an uncertain parameter, stochastic programming was used in Schwartz *et al.* (2016) and in Menke (2017) to solve PSP considering demand as stochastic variable. However, stochastic programming is not suitable for problems with high number of possible solution such as PSP.

In Price and Ostfeld (2015) and Price and Ostfeld (2016), PSP was modeled using graph theory and solved using deterministic Dijkstra's algorithm. Graph model requires the decision variables to be discrete which is not compatible with PSP nature that has mixed integer decision variables.

Goal Programming (GP) is a multi-objective linear programming (LP) in which each objective is assigned a target value and the goal is to minimise the deviation between the achieved and the target values of each objective. GP is computationally efficient and can optimise more than one objective simultaneously. It is becoming increasingly popular in the field of multi-decision making because it is relatively straightforward. The earliest development of a GP was introduced by Chrarnes et al. (1955). There are three types of GP which are Lexicographic GP, Weighted GP and Chebyshev GP (Jones and

Tamiz 2010). The three types of GP are combined in one general framework called Extended Lexicographic GP (ELGP) by Romero (2001) and Romero (2004). Recently, GP was used to allocate technicians to tools in factories (Ignizio 2004), to schedule the tour of a marketing executive (Mathirajan and Ramanathan 2007), to schedule batch processing machines (Petrovic and Aköz 2008), and to minimise operational cost in rural farms (Sharma et al., 2006). In this thesis, GP will be used for the first time in literature (according to our best knowledge) to solve PSP.

## 2.4.2 Heuristic Optimisation Methods

In this subsection, heuristic optimisation methods that were used to solve PSP will be explored. Heuristic optimisation methods search in huge space; thus taking long computational time to find optimal solution. Global optimality is not guaranteed, unless the method evaluates all possible solutions, which is computationally not efficient for large real WDS. Additionally, most heuristic optimisation methods have several parameters that need to be tuned pre optimisation. There is no deterministic method that can find the optimum values for these parameters. Tuning can be time consuming process and it affects balancing between intensification and diversification of the searching process.

Heuristic optimisation methods which were used to solve PSP are dynamically dimensioned search (Abdul Gaffoor 2017); hill climbing (Van Zyl 2001; Van Zyl *et al.,* 2004), greedy algorithms (McCormick and Powell 2003a; Giacomello *et al.,* 2012), improved limited discrepancy search (Ghaddar *et al.,* 2015; Naoum-Sawaya et al., 2015), grid search (Bagirov et al., 2013), Hooke and Jeeves pattern search (Bagirov et al., 2013), and adaptive search (Pezeshk and Helweg 1996). These methods are also known as local search methods because they are usually used to find local optimum solution. These methods can be easily trapped in local optimum solutions.

Metaheursitic optimisation methods are more guided heuristics that diversify the search space to avoid being trapped in a local optimum solution. They were used extensively to solve PSP. They can be classified using different criteria (Birattari et al. 2001). The most common criterion is the population-based vs.

single-point search (Maier et al. 2014). A recent review of metaheuristics which are used for environmental models including water is available in Maier et al. (2018). The following texts explore the differed metaheuristic methods that were used to solve PSP.

Genetic Algorithms (GA) is a type of Evolutionary Algorithms that was used broadly in water resources planning and management (Maier et al., 2015; Nicklow et al., 2010). GA is inspired by Darwin mechanics of natural selection. Many PSMs in literature relays on GA (Beckwith and Wong 1995; Mackle *et. al.,* 1995; Lingireddy and Wood 1998; Schaetzen et al., 1998; Atkinson *et al.,* 2000; Shamir et al., 2004; Lopez-Ibanez et al., 2011; Jung et al., 2014; Luna et al., 2018). Different variants of GA was utilised to boost the performance of GA in solving PSP, like fast messy GA (Wu 2007; Wu et al., 2009) and micro GA (Bene et al., 2010; Selek et al., 2012). GA has parameters that need to be tuned in advance such as number of generations, population size, mutation rate, and cross-over rate.

Ant colony is an optimisation method inspired by the foraging behaviour of ants. This optimisation method had been utilised to solve PSP in Ostfeld and Tubaltzev (2008), López-Ibáñez et al., (2008), López-Ibáñez (2009), Prasad *et al.,* (2012), and Hashemi (2013a). A comprehensive review of Ant Colony optimisation applications in water resources planning and management is available in Afshar *et al.* (2015). Ant colony optimisation has parameters that need to be tuned in advance such as number of ants, pheromone evaporation rate, and pheromone reinforcement rate.

Particle swarm optimisation is inspired by the journey of searching for food in flocks of birds. It was used in the following researches to solve PSP (Wegley *et al.,* 2000; Al-Ani and Habibi 2012; Brentan *et al.,* 2013; Brentan and Luvizotto Jr. 2014; Tang *et al.,* 2014; Rajabpour et al., 2015). Particle swarm optimisation has parameters that need to be tuned in advance such as inertia coefficient, initial position, initial velocity, and number of particles.

Simulated annealing is a metaheuristic optimisation method that is inspired by the cooling process of metals. It is a single point search (trajectory method) not a population based like other metaheuristics. Simulated annealing was used in Goldman (1998), McCormick and Powell (2004), Sousa et al. (2006), Goldman and Mays (2012), Khatavkar and Mays (2017) to solve PSP. Simulated annealing has parameters that needs to be tuned to ensure getting optimum solution such as initial temperature, length of Markov chains, and temperature reducing rate. In Torregrossa and Capitanescu (2019), authors concluded that particle swarm and simulated annealing gave lower energy cost pump schedules than genetic algorithms.

Harmony search is a metaheuristic optimisation method inspired by improvisation of Jazz musicians. Harmony search algorithm was used in Kougias and Theodossiou (2012), and De Paola *et al.,* (2016) to solve PSP. Parameters that need to be tuned are harmony memory, consideration rate, and pitch adjusting rate.

Grey wolf algorithm is a recent meta-heuristic optimisation method inspired by hunting behaviour of grey wolves. It has been utilised recently in Liu et al. (2018) to optimise the operation of cascade pumping stations in water systems that have inverted siphons and open channels.

### 2.4.3 Other Optimisation Methods

This subsection explores the hybrid optimisation methods, multi-objective optimisation methods, and model predictive optimisation methods that were used to solve PSP.

Mathematical optimisation methods are often trapped in a local optimum solution but they are computationally efficient. On the other hand, heuristic optimisation methods are global optimisation methods but they are typically computationally inefficient. Thus, several PSMs integrate mathematical optimisation methods and heuristic optimisation methods in one hybrid optimisation method.

Pasha and Lansey (2010) and Pasha and Lansey (2014) used linear programming and historical pump schedules to generate warm solutions that can be used to generate initial population for an evolutionary algorithm named as shuffled frog-leaping algorithm (SFLA). Operational staff experience was used as initial solution in some pump scheduling methods including recent ones

(Bagloee *et al.,* 2018; Luna et al., 2018). In Van Zyl (2001) and Van Zyl et al. (2004) GA is combined with two hill-climbing methods (the Hooke and Jeeves and the Fibonacci) to improve local search. In Giacomello *et al.* (2012) optimum pump station flow obtained from LP is used to feed Greedy Algorithm to obtain discrete pump schedule. In Puleo (2014), optimal pump schedule obtained from LP was used to seed separately two heuristic optimisation methods: hybrid discrete dynamically dimensioned search (HD-DDS) and GA. Bagloee *et al.* (2018) coupled integer linear programming and mixed integer nonlinear programming with machine learning techniques to find optimum values for the continuous variables of valves flow and pumps speed. The optimisation method can incorporate operation rules which are based on operators' experience and common practices.

For real-time operation, single objective pump scheduling is usually preferred because operators do not have enough time to decide the best solution among a set of optimum solutions. However, for offline analysis and operation development, multi-objective pump scheduling is desired to investigate the trade-off between the different objectives of PSP.

Different multi-objective optimisation methods were used to optimise more than one objective of PSP simultaneously, such as Multi-Objective Genetic Algorithm (MOGA) (Savic *et al.,* 1997; Kelner and Leonard 2003; Baran et al., 2005; Ewald et al., 2008; Wang et al., 2009; Giustolisi et al., 2012), Non-Dominated Sorting Genetic Algorithm II (NSGA-II) (Prasad et al., 2004; Baran et al., 2005; Alfonso et al., 2010; Mala-Jetmarova *et al.,* 2014; Mala-Jetmarova *et al.,* 2015; Stokes et al., 2015a; Ashbolt et al., 2014; Ashbolt et al., 2016; Makaremi et al., 2017; Castro-Gama et al., 2017; Ashbolt and Perera 2018), Strength Pareto Evolutionary Algorithm (Baran et al., 2005) , Strength Pareto Evolutionary Algorithm (SPEA) (Carrijo et al., 2004), Strength Pareto Evolutionary Algorithm II (SPEA2) (Lopez-Ibanez et al., 2005; Kurek and Ostfeld 2013), Multipurpose fuzzy LP (Arai *et al.,* 2012), Particle swarm optimisation method (Al-Ani and Habibi 2012), Harmony search algorithm and Polyphonic harmony search algorithm (Kougias and Theodossiou 2012; De Paola *et al.,* 2016), Multialgorithm genetically adaptive method (Odan et al., 2015).

Pareto optimality is not guaranteed due to uncertainties caused by parameters tuning, selection, and clustering procedures. Different metrics can be used to evaluate the performance of multi-objective optimisation methods in solving PSP (Lucken et al., 2004; Baran et al., 2005; Kougias and Theodossiou 2012).

In Abiodun and Ismail (2013), two objectives (energy cost and maintenance cost) were added up in a single objective function using adaptive weighting factors. Authors stated that the adaptive weighting factors ensures that no objective dominates the other.

Model predictive control is an iterative method usually used to control a process. Recently, it has been used solve PSP (Duzinkiewicz et al., 2005, Wang and Brdys 2006; Drewa et al., 2007; Van Staden *et al.,* 2009; Van Staden *et al.,* 2011; Ocampo-Martinez et al., 2013; Fiorelli et al., 2013; Brdys et al., 2013; Sun et al., 2015; Alarfaj and Bhattacharya 2018). Unlike mathematical and heuristic optimisation methods, optimality in model predictive control method is achieved by stability of the process. A good review for model predictive control method and its advantages and disadvantages in solving PSP is available in Menke (2017) and Abdul Gaffoor (2017).

## 2.4.4 Optimisation Software

The previously discussed modules (hydraulic and water quality modelling, pump scheduling optimisation modelling, pump scheduling optimisation methods) play major role in determining the effectiveness and the computational efficiency of any PSM. Other important factors that have impact on the computational efficiency of the PSM are the computer software, the programming language, and the random access memory (RAM) of the computer.

Multi-core computers have become popular. Thus, several PSMs started to utilise parallel computing to increase computation efficiency, especially for heuristic optimisation methods which requires intensive evaluation of many possible solutions such as Genetic Algorithms in Wu and Zhu (2009), Ant Colony Optimisation in Lopez-Ibanez et al. (2012), Dynamically Dimensioned Search in Abdul Gaffoor (2017), six different Multi-Objective Revolutionary

Algorithms in Lucken et al. (2004). Parallel computing was also used to increase the computational efficiency of some mathematical optimisation methods that requires large number of evaluations, like Stochastic Programming in Ibarra and Arnal (2014).

Several pump scheduling software for WDSs exist, like: FINESSE (Bounds et al., 2003; Bounds *et al.,* 2006), Darwin Scheduler (Kampa and Dringoli 2017), Darceto (Darceto 2016), WATERNET (Cembrano et al., 2000); H2ONET Scheduler (Boulos *et al.,* 2001; Hartely 2007), WaterCAD (Walski 2001), WATCHMAN (Dellow 1990; Slipper 1991; ), MS Excel add-ins (Tischer et al., 2003; EXETER ADVANCED ANALYTICS LLP 2013 ; Savić et al., 2011; Giustolisi et al., 2011), ENCOMS (Rao et al., 2007), Gondwana (Thienen and Vertommen 2015), KYPUMP (Chase and Ormsbee 1993), Pumplan (Likeman 1990; Moore 1991), Aquatoria (Aquatoria 2014), EXPLORE (Leon 2000), MISER (Ganidi and Holden 2014), PLIO (Cembrano et al., 2011), SIWA Optim (SIEMENS 2018), and BalanceNet from Innovyze (2019). These software might be powerful. However, the optimisation methodologies and approximations which are used in these software are hidden, which makes us uncertain about the optimality of their solutions.

## 2.5 Summary

This chapter explores most notable works in optimising the operation of pumps in WDSs. The three main modules that form any pump scheduling method were studied. These modules are hydraulic and water quality modelling, pump scheduling optimisation modelling, pump scheduling optimisation methods.

This literature review concluded that each of the existing pump scheduling method has its own merits and demerits. There seems to be no ideal approach for pump scheduling problem. The field is still open for researchers to find more unique approach for this problem. In the meantime, decision maker can choose the most suitable PSM based on his/her preferences.

Mala-Jetmarova *et al.* (2017) wrote a systematic review in a tabular form for more than 200 papers about pump scheduling. A continuation for that review is available in the Appendix of this thesis. Other worthwhile comprehensive literature reviews about pump scheduling in WDSs are available in Coulbeck (1977), Ormsbee and Lansey (1994), Nitivattananon (1994), Pelletier (1995), Goldman (1998), van Zyl (2001), Lansey (2008), López-Ibáñez (2009), AbdelMeguid (2011), Gleixner *et al.* (2012), D’Ambrosio *et al.* (2015), Menke (2017), Abdul Gaffoor (2017), and (Sunela 2017).

# Chapter 3: Methodology

## 3.1 Introduction

This chapter aims to describe the new pump scheduling method that is developed to solve pump scheduling problem. In section 3.2, pump scheduling problem is defined and assumptions that are used to relax the problem are mentioned. In section 3.3, the pump scheduling optimisation problem is formulated by defining the decision variables, the objective function, and the constraints. In section 3.4, the solution steps for the problem are mentioned sequentially. Section 3.5 gives summary for the whole chapter.

## 3.2 Problem Definition and Assumptions

Pump scheduling is the process of determining when to start/stop each pump in a WDS to achieve certain objectives. Pump scheduling problem is formulated and solved in this research as a multi-objective optimisation problem. The objectives are minimising energy cost and water age. These objective are subjected to essential constraints (e.g. conservation of mass and energy) and optional constraints (e.g. water level in the tank between predefined minimum and maximum levels), as shown in the next section.

As discussed in Chapter 1, pump scheduling problem is an NP-hard problem and hence cannot be easily solved by hand, especially for large real WDSs. In order to solve this NP-hard problem in a computationally efficient manner and without loss of optimality, PSP need to be carefully formulated. In this research, the developed pump scheduling method uses the following assumptions to relax the PSP:

1- The pump scheduling time horizon was divided pre-optimisation into fixed length time steps (e.g. 1 hour). During each time step, pumps' flow (and hence pumps' head, efficiency, power) are assumed constant regardless of changes in the network during the time step (e.g. changes in water levels in tanks which should cause changes in pumps flow). The assumption is compatible with the gradual changes observed in real WDSs. This assumption is also compatible with methods of solving

WDSs hydraulics (Todini and Pilati 1987) in which flows are assumed constant during each hydraulic time step. This assumption was used in many previous PSMs (McCormick and Powell 2004).

2- FSPs and VSPs are allowed to switch on at the beginning of each time step only. This is done because giving the freedom for pumps to switch on at any time will increase the number of possible solutions vastly. This of course can lead to suboptimal solutions, because an optimum pump switch can be at any time during the time step. To increase the optimality of the solution, FSPs are allowed to run for a fraction of time step, i.e. FSPs can stop any time before the end of a time step. The same does not apply to VSPs, because varying the speed and the fraction of time step during which VSP is running will increase the problem size significantly. Another way to increase the optimality of the solution, is to shorten the length of the time steps (e.g. 30 minutes instead of 1 hour). Reducing the time step length is not expected to significantly increase the computation time because the developed pump scheduling method is based on goal programming (GP) which is a computationally efficient method.

3- The developed pump scheduling method is not coupled with a demand forecasting method as it would shift the focus of this research. Instead, water demand during each time step of the scheduling time horizon is assumed known pre-optimisation. This is not compatible with the fact that water demand in WDSs changes instantaneously. Having said this, the developed pump scheduling method is computationally fast and can be used in the real-time setup where demands forecasts are updated frequently (e.g. every hour).

4- Minimum pressure at demand nodes is not constrained. It is assumed that the analysed WDS is well designed, so that pressure at demand nodes is always above the minimum requirement, regardless of the number of running pumps and water level in tanks. This assumption was also used in some of the previously developed PSMs (Goryashko and Nemirovski 2014; Jowitt and Germanopoulos 1992). This assumption works well in WDSs where consumers get water from roof tanks not directly from the network.

If the assumption of well-designed WDS is not valid then the minimum water level in tanks can be increased to increase the pressure in the network.

5- Maximum demand charge for electricity is not considered in the methodology, thus the method may result in a higher than optimal maximum demand charge. This assumption is often made in relevant literature (Moreira and Ramos 2013; Menke et al., 2016).

6- VSPs are allowed to run at relative speeds which are in the range 0.7 to 1.0. This assumption is made due to the following:

    - It is not recommended to operate VSPs at speeds lower than 0.7. This is because the efficiency of a VSP is high and almost constant for relative speeds above 0.7 (Sarbu and Borza 1998; Walski et al., 2003; Marchi et al., 2012; Simpson and Marchi 2013). When relative speed decreases below 0.7, pump efficiency decreases significantly (Marchi and Simpson 2013, Coelho and Andrade-Campos 2016).
    - Efficiency of variable frequency drive (VFD), the most common system used to alter the speed of a VSP motor, is usually constant and ranges between 95% and 98% when pump relative speed is high, i.e. above 0.7 (Ulanicki et al., 2008). Efficiency of motor is also around its maximum when pump relative speed is high, i.e. above 0.7 (Kaya et al., 2008; Kalaiselvan et al., 2016).

    This assumption (relative speed of VSPs is constrained between 0.7 and 1.0) was also used in a pump scheduling method developed in Blinco et al. (2016).

7- In light of the previous assumption, the PSM developed in this research considers the VSP efficiency as variable with flow only. Efficiency of VFD and motor are considered constant. Other efficiencies that vary with speed such as efficiency of electric cables (Moreno et al., 2007), efficiency of pump-motor coupling (e.g. magnetic coupling, oil coupling), losses due to pump-motor vibrations (Luo et al., 2012) are not considered in energy consumption calculations.

8- Water age is used as surrogate indicator of water quality. This assumption is made due to the following:

- The major improvement of water quality is usually done at treatment plants. After leaving the treatment plant, water age is the main parameter that effects water quality in WDSs. When water age increases, bacterial growth increases, disinfection by-products increase, and residual chlorine decreases (U.S. Environmental Protection Agency 2002). The same assumption was used in many past works on operational WDS optimisation (e.g. Marchi et al., 2014; Murphy et al. 2007).
- Water age analysis doesn't require additional water quality calibration for the hydraulic model.
- Water age is directly proportional to time. It is considered as zero-order reaction. This will simplify the optimisation and reduce the computation time.

9- Water age in WDSs is reduced implicitly in two different ways:
   - By reducing tanks maximum water level (Kennedy, et al. 1993; Price and Ostfeld 2016) which prevents storing big amounts of water for long time. However, this method might reduce pressure at demand nodes. Additionally, the method might not be safe for emergency cases or might not be suitable for maintenance programs when more water in tanks is required to overcome shortage in the network.
   - The alternative way is to keep tanks maximum water level as it is and to minimise tanks inlet/outlet flow to a rate that does not harm water age in tanks themselves. This, in turn, allows demand nodes to receive fresh water directly from sources (not tanks) and enables supplying sufficient water in tanks for emergency/planned cases.

Several researchers noted the negative affect of tanks on water quality (Walski 2001; Olson and DeBoer 2011). This is because tanks increase water age in WDSs. Clark et al. (1994) indicate that the longer the water resides in the system, the more likely its quality will deteriorate. Clark et al. (1993), Howie (2008), Lansey (2008) pointed out that chlorine in WDSs can be improved through exercising the operation of tanks and pumps, without the need to add/manipulate chlorine boosters. Oversized pipes have also negative affect on water quality because they increase water age. The path that water follow in WDSs has additional impact on water quality (Prasad and Walters 2006), e.g. longer path increases water age.

The above two approaches do not take water age into account during the optimisation. Instead, water age at demand nodes is evaluated post-optimisation. The objective of these approaches is to show the effectiveness of pump scheduling as an important strategy not only to minimise energy consumption, but also to improve water quality, without the need to add/modify treatment process in WDSs. Additionally, these approaches allow to improve water quality in a computational efficient manner without using the non-linear equations of reactions.

Note that the above assumptions reduce the likelihood of obtaining the global optimum pump schedules but they increase the computational efficiency. Global optimality is given up here for the sake of having a computationally fast method that can be used for real-time control of large real WDSs. Nevertheless, the concept of global optimality is questionable anyway due to several uncertainties that exist in WDSs, e.g. uncertainty in model calibration and uncertainty in water demand, to name a few. Above all, the preceding assumptions do not cause loss of feasibility of solutions, which is probably more important than the global optimality and computational efficiency. Feasibility of solutions is assured by running a hydraulic solver post optimisation. The ultimate evidence for the quality of solutions obtained from the developed PSM can be found in the results of the case studies (Chapter 4) which clearly demonstrate the benefits of the developed PSM.

## 3.3 Pump Scheduling Problem Formulation

According to our best knowledge, for the first time in the literature, pump scheduling optimisation problem is formulated and solved as a Goal Programming (GP) optimisation problem.

The objective in GP is to minimise the deviation between the target and the achieved values for each objective. Objectives in GP are added up to form a single objective function. Note that GP requires all equations (objective function and constraints) to be linear. Additionally, the weight of each objective needs to be carefully specified to avoid getting Pareto inefficient solution. Thus, the PSP in this thesis is driven by the minimization of the following objective function:

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

where $PEC_i$ = positive deviation variable for energy cost objective (£); $w$ = weighting factor; $PVC_{a,t,i}$ = positive deviation variable for tank water volume change objective (m$^3$); $NVC_{a,t,i}$ = negative deviation variable for tank water volume change objective (m$^3$); $i$= iELGP iteration index; $I$= total number of iterations; $a$ = tank index; $A$ = total number of tanks; $t$ = time step index; and $T$ = total number of time steps.

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

$$PEC_i = AEC_i - ECT \qquad \forall i \in I \qquad (2)$$

where $AEC_i$ = achieved energy cost (£); and $ECT$ = energy cost target (£).The energy cost target is a constant and it is calculated pre-optimisation as will be described in the next section (3.4). The energy cost target has an ideal optimistic value that cannot be reached in real life. Thus, the achieved energy cost will always deviate positively from the energy cost target.

The achieved energy cost for VSP and FSP is calculated as follows:

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

where $P_{v,t,i}^{\substack{Actual\\Speed}}$ = VSP power at actual speed (kW); $v$ = VSP id; $V$ = total number of VSPs; $P_{f,t,i}$ = FSP power (kW); $X_{f,t,i}$ = decision variable denoting pump $f$ status; $f$ = FSP id; $F$ = total number of FSPs; $E_t$ = energy cost during time step *t* (£/KWh); and $L_t$ = time step length (hr).

As mentioned in section 3.2, affinity laws provide good approximation for VSPs when they run at high speed. This is because relative efficiency (efficiency at actual speed over efficiency at maximum speed) is almost 1 (i.e. efficiency does not change) when VSP run at high speed. Affinity law which alter pump power with pump speed is almost linear when pump relative speed is between 0.7 and 1.0 as shown in Figure 2.

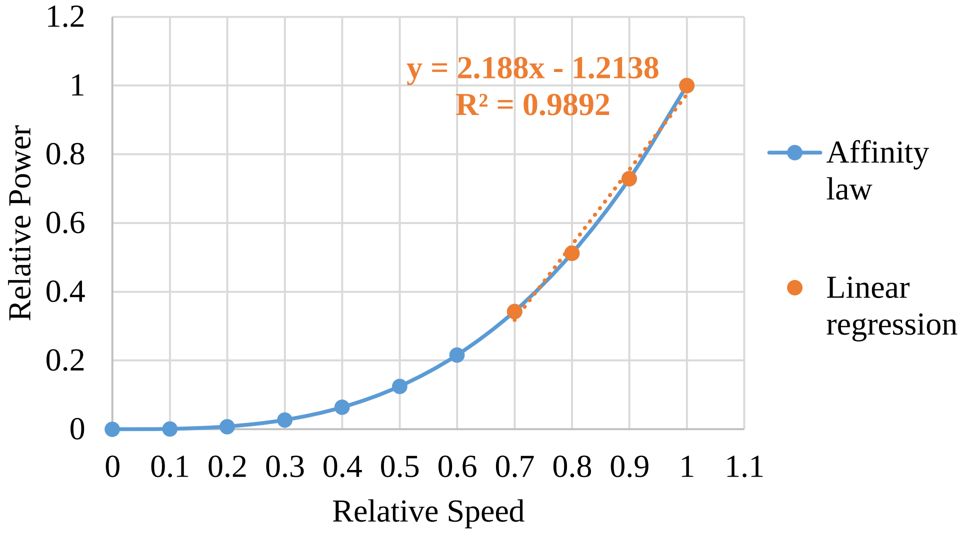


Figure 2. Linear regression between pump relative power and relative speed

Thus, it is convenient to fit the following regression line:

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

Where $s$ = the slope of the fitted regression line which is equal to 2.1880; $X_{v,t,i}$ = decision variable denoting pump $v$ relative speed; $y$ = the y-intercept of the fitted regression line which is equal to 1.2138; $B_{v,t,i}$ = binary variable that is equal to zero when pump is not running and equal to one when pump is running; and $P_{v,t,i}^{Maximum\ Speed}$ = VSP power at maximum speed (kW).

The coefficient of determination for the fitted regression line in Eq. (4) is equal to 0.9892, which means that Eq. (4) is very close to affinity law that alter pump power with speed. The previous constant values ($s$ = 2.188, $y$ = 1.2138, coefficient of determination = 0.9892) are obtained from the fitted linear regression line shown in Figure 2.

Note that the values of $S$ and $y$ are nearly constant for a VSP running at relative speed between 0.7 and 1.0. However, the same cannot be claimed when VSP relative speed is below 0.7.

The relative speed of VSP is constrained as follows:

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

Pump speed $X_{v,t,i}$ in Eq. (5) is considered as semi-continuous variable, because it either 0 or any real value between 0.7 and 1.0. Optimum values for $X_{v,t,i}$ are found during the optimisation using Branch and Bound method (Land and Doig 1960).

Note that in case the VSP is under-sized, then the minimum relative speed can be increase to more than 0.7 to ensure that shutoff head is larger than static head and to avoid having zero flow. If VSP is over-sized (relative speed 0.7 gives pressure higher than required), then Eq. (5) might result in higher energy consumption and might increase pressure and leakages in the network.

The second term in Eq. (4) is multiplied by a binary variable $B_{v,t,i}$ to make pump power $P_{v,t,i}^{Actual\ Speed}$ equal to 0 when pump speed $X_{v,t,i}$ is equal to 0. The binary variable $B_{v,t,i}$ should be equal to 1 when pump speed is not 0. Thus, $B_{v,t,i}$ is tied with $X_{v,t,i}$ using the following two equations:

$$B_{v,t,i} \geq X_{v,t,i} \qquad \forall v \in V, \forall t \in T, \forall i \in I \qquad (6)$$

$$B_{v,t,i} \leq \frac{s}{y} . X_{v,t,i} \qquad \forall v \in V, \forall t \in T, \forall i \in I \qquad (7)$$

The VSP power at maximum speed in Eq. (4) can be calculated as follows:

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

where $\gamma$ = specific weight of water (kN/m$^3$); $Q_{v,t,i}^{Maximum\ Speed}$ = pump $v$ flow rate (m$^3$/h) at maximum speed; $H_{v,t,i}^{Maximum\ Speed}$ = pump $v$ head (m) at maximum speed; and $\eta_{v,t,i}^{Maximum\ Speed}$ = pump $v$ efficiency at maximum speed. Pump operating point will be found using hydraulic simulator as shown in the next section (3.4).

For a group of parallel identical VSPs, which is common in pumping stations, pumps should run at the same relative speed (Georgescu and Georgescu 2015). By doing this, flow/load will be distributed equally between all running pumps in that group. This in turn reduces energy consumption (Jones et al., 2008; Koor et al., 2016), number of iterations, and computation time.

Since the decision variable $X_{v,t,i}$ is semi-continuous, it is not possible to impose a constraint that equalises all decision variables of parallel identical VSPS. It is because a pump in a group of parallel identical VSPs could have 0 relative speed and other pumps could have non-zero relative speed. This problem is solved here by re-modelling parallel identical VSPs into combined pumps. Each combined pump has characteristics (i.e. head, efficiency, power curves) of a certain number of pumps. For example, a group of two identical parallel VSPs should be re-modelled into two combined pumps. The first combined pump has characteristics of one pump. The second combined pump has characteristics of two pumps in parallel. Only one combined pump is allowed to run at a time. Thus, the following constraint should be used for every group of remodelled parallel identical VSPs:

$$\sum_{cv=1}^{CV} B_{cv,t,i} \leq 1 \qquad \forall t \in T, \forall i \in I \qquad (9)$$

where $cv$ = index of a combined VSP; and $CV$ = total number of combined VSPs. Eq. (9) implies that the summation of binary variables $B_{cv,t,i}$ for combined pumps should be 0 (all combined pumps are off), or 1 (one of the combined pumps is on).

Unlike VSPs, the decision variable $X_{f,t,i}$ for FSPs in Eq. (3) is the fraction of time step during which the pump is running. The decision variable $X_{f,t,i}$ is constrained as follows:

$$0 \leq X_{f,t,i} \leq 1 \qquad \forall f \in F, \forall t \in T, \forall i \in I \qquad (10)$$

If $X_{f,t,i}$ is 0 or 1, then pump is off or on during the whole time step, respectively. If $X_{f,t,i}$ is between 0 and 1, then pump is on from the beginning of the time step for duration equals to $X_{f,t,i}L_t$ then it is off until the end of the time step. The other option which is to have FSP off at the beginning of the time step, then to turn it on for duration equals to $X_{f,t,i}L_t$ until the end of the time step is not considered. This is because having this option will increase the computation time, without significant improvement in optimality, especially for the usual time step length of 1 hour.

The FSP power at maximum speed in Eq. (3) can be calculated as follows:

$$P_{f,t,i} = \frac{\gamma Q_{f,t,i}\, H_{f,t,i}}{\eta_{f,t,i}} \qquad \forall f \in F, \forall t \in T, \forall i \in I \qquad (11)$$

where $Q_{f,t,i}$ = pump $f$ flow rate ($m^3$/h); $H_{f,t,i}$ = pump $f$ head (m); and $\eta_{f,t,i}$ = pump $f$ efficiency. Pump operating point will be found using hydraulic simulator as shown in the next section (3.4).

For a group of parallel identical FSPs, which is common in real pumping stations, it does not matter (from energy cost optimisation point of view) which pump is started or stopped during a given time step. What matters is the number of running pumps during each time step. This concept was used here to reduce the number of decision variables and hence reduce the number of optimisation iterations and the overall computational time required. Thus, the following constraint is used to specify the order of switching for a group of parallel identical FSPs.

$$X_{gf,t,i} \geq X_{gf+1,t,i} \geq \cdots \geq X_{GF,t,i} \qquad \forall t \in T, \forall i \in I \qquad (12)$$

where $gf$ = pump index in a group of parallel identical FSPs; and $GF$ = total number of pumps in a group of parallel identical FSPs. Once the number of pumps in a pumping station is optimised for each time step, the operator can decide which pump(s) to run, e.g. based on a number of total running hours, maintenance plans, etc.

It is well known that higher number of pump switches increases maintenance cost due to increased wear and tear of pumps. It is difficult to define as a linear constraint because turning a pump from on to off is not considered as a pump switch. To solve this problem, pump switches are constrained here implicitly by increasing the length of time steps, i.e. by controlling the number of time steps. For example, assume that the optimisation time horizon is 24 hours and the maximum allowed number of pump switches is 3. If 3 time steps are used for scheduling then the number of pump switches cannot be more than 3 because a pump is allowed to switch on only once in each time step. The consequences of constraining pump switches in this way are discussed further in the next chapter 4 in section 4.3.4.

Similar to Eq. (2) for energy cost positive deviation variable, the positive and negative deviation variables for water volume changes in tanks ($PVC_{a,t,i}$ and $NVC_{a,t,i}$ in Eq. (1)) are defined using the following equations:

$$NVC_{a,t,i} - PVC_{a,t,i} = VCT_a - VC_{a,t,i} \qquad \forall a \in A, \forall t \in T, \forall i \in I \tag{13}$$

$$NVC_{a,t,i} \geq 0 \quad , \quad PVC_{a,t,i} \geq 0 \qquad \forall a \in A, \forall t \in T, \forall i \in I \tag{14}$$

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

In Eq. (13), the achieved water volume change in a tank $VC_{a,t,i}$ is positive when tank gains water or negative when tank drains water. The target water volume change in a tank $VCT_a$ is set to a very small value (~0) as described in the next paragraph. Eq. (14) enforces both $PVC_{a,t,i}$ and $NVC_{a,t,i}$ to be positive. When $VC_{a,t,i}$ is positive (tank is gaining water), and $VCT_a$ is a very small value (~0), then $NVC_{a,t,i}$ will be 0 (it can't be negative as per Eq. (14)) and $PVC_{a,t,i} = VC_{a,t,i}$. If $VC_{a,t,i}$ is negative, then $PVC_{a,t,i}$ will be 0 (it can't be negative as per Eq. (14)) and $NVC_{a,t,i} = -VC_{a,t,i}$. Note that both $PVC_{a,t,i}$ and $NVC_{a,t,i}$ cannot take positive values simultaneously, because a tank is either loosing or gaining water during a time step.

The purpose of the weighting factor $w$ in Eq. (1) is to normalise the two objectives (energy cost and water volume change in tanks) so that they can be added up. In GP, the weighting factor of an objective is usually set equal to the reciprocal of the target value of that objective (Romero 1991). In this case, the weighting factor $w$ in Eq. (1) is equal to the reciprocal of the target value of tanks water volume change $VCT_a$. To get a Pareto efficient solution, $VCT_a$ is required to be an optimistic value. The optimistic value of $VCT_a$ is zero, which means that the target is not to gain or drain water from tank $a$. However, the weighting factor will be the reciprocal of 0. Thus, the value of $VCT_a$ is set to a small amount of 1 m$^3$, to avoid division by 0. The weighting factor $w$ can be increased or decreased by the decision maker to reflect his/her attitude toward balancing the two objectives and to avoid worsen water age inside tanks. This matter is discussed in more details in section 4.4.4 in Chapter 4.

To decrease the number of variables and to increase the computational efficiency, tank water volume change $VC_{a,t,i}$ in Eq. (13) can be calculated by relating it to pumps' flows and demands, as shown in the following equation:

$$VC_{a,t,i} = \left( \left( \sum_{v=1}^{V} Q_{v,t,i}^{\substack{Max. \\ Speed}} . X_{v,t,i} \right) + \left( \sum_{f=1}^{F} Q_{f,t,i} . X_{f,t,i} \right) - D_{a,t} \right) . L_t$$

$$\forall a \in A, \forall t \in T, \forall i \in I \qquad (15)$$

where $D_{a,t}$ = total demand from tank $a$ 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 $X_{v,t,i}$ according to Affinity Laws. If a pump draws water from tank $a$, then its flow value in Eq. (15) is negative.

Water volume in each tank is constrained based on the tank capacity as shown in the following equation:

$$V_{a,min} \leq \left( \sum_{t=1}^{t} VC_{a,t,i} \right) + V_{a,initial} \leq V_{a,max} \qquad \forall a \in A, \forall t \in T, \forall i \in I \qquad (16)$$

where $V_{a,min}$ = minimum water volume of tank $a$ ($m^3$); $V_{a,initial}$ = initial (at the beginning of the optimisation time horizon) water volume in tank $a$ ($m^3$); $V_{a,max}$ = maximum water volume of tank $a$ ($m^3$).

If final water volume in a tank (i.e. tank volume at the end of the optimisation horizon) is less than its initial water volume, then the energy cost is reduced at the expense of a water volume in that tank (which can run out of water after operating a number of days like this). The following constraint is used to ensure that the final water volume in each tank is at least equal to its initial water volume:

$$\sum_{t=1}^{T} VC_{a,t,i} \geq 0 \qquad \forall a \in A, \forall i \in I \qquad (17)$$

The following mass balance constraint between water supplied by pumps and water demand is used for a pressure zone that does not have a tank:

$$\left(\left(\sum_{v=1}^{V} Q_{v,t,i}^{\substack{Max.\\Speed}} . X_{v,t,i}\right) + \left(\sum_{f=1}^{F} Q_{f,t,i} . X_{f,t,i}\right) - D_t\right) . L_t = 0 \qquad \forall t \in T, \forall i \in I \quad (18)$$

Finally, the spatial distribution of chlorine at demand nodes is quantified using the weighted average chlorine as follows:

$$WAC = \frac{\sum_n^N \sum_t^T k . Q_{n,t} . C_{n,t}}{\sum_n^N \sum_t^T Q_{n,t}} \quad (19)$$

where $WAC$ = weighted average chlorine in the network (mg/l); $Q_{n,t}$ = water demand in node $j$ (m$^3$/hr); $C_{n,t}$ = chlorine in node $n$ (mg/l); $n$ = node index; $N$ = total number of nodes; and $k$ = constant that equals to 1 if $C_{n,t}$ is above a predefine chlorine threshold, or 0 otherwise. Two factors affect the weighted average chlorine in Eq. (18), which are demand and chlorine at nodes. Nodes with high water demand have more impact on the weighted average chlorine than nodes with low demands. Nodes that have chlorine less than the predefined threshold reduce the weighted average chlorine. A similar metric can be used to quantify the spatial distribution of water age at demand nodes (Marchi et al., 2014).

The hydraulic and water quality simulation software *EPANET 2.0.12* is used to calculate mass balance, energy balance, and water quality equations that are not presented in the previous equations, as shown in the next section (3.4).

## 3.4 Pump Scheduling Method

The pump scheduling problem defined in the previous two sections is solved here using the iELGP optimisation method shown in Figure 3. The Extended Lexicographic GP (Romero 2001, 2004) is used in this thesis to give decision maker more flexibility and choices to solve the PSP. The ELGP used here runs iteratively to update decision variable values hence was named iterative ELGP or iELGP.

The iELGP method starts by setting the value for energy cost target $ECT$. This value needs to be specified carefully. If it is set too pessimistically then the solution will be Pareto inefficient. On the other hand, if it is set too optimistically (e.g. set equal to zero) then the method will focus on the energy cost target and will not optimise the other target (water volume change in tanks). The energy cost target $ECT$ is set here to an ideal optimistic value that cannot be reached in real life. This value is calculated based on the assumption that all pumps always run at their best efficiency points (BEPs), as shown in the following steps:

1- Set iteration index $i = 1$.

2- For each VSP, find values of flow and head at BEP and maximum speed using pump characteristic curves. Substitute these values in Eq. (8) to calculate pump power $P_{v,t,i}^{Maximum\ Speed}$. In the first iteration, each VSP has the same $P_{v,t,i}^{Maximum\ Speed}$ for all time steps.

   Substitute $P_{v,t,i}^{Maximum\ Speed}$ in Eq. (4).

3- For each FSP, find values of flow and head at BEP. Substitute these values in Eq. (11) to calculate pump power $P_{f,t,i}$. In the first iteration, each FSP has the same $P_{f,t,i}$ for all time steps.

4- Using Mixed Integer Linear Programming (MILP), find the optimum decision variables for each VSP and FSP during each time step (i.e. $X_{v,t,1}$ and $X_{f,t,1}$) that gives the minimum energy cost $AEC_1$, where Eq. (3) is the objective function to be minimized and Eqs. (4), (5), (6), (7), (9), (10), (12), (15), (16), (17) and (18) are the constraints.

5- Set energy cost target $ECT$ equals to achieved energy cost $AEC_1$ which is found in the previous solution step 4.

The optimum decision variables ($X_{v,t,1}$ and $X_{f,t,1}$) which are found in solution step 4 rely on the unrealistic assumption that pumps run always at their BEPs. Therefore, pumps' operating points are adjusted based on the feedback from the hydraulic simulator, as shown in the following solution steps (see also flow chart in Figure 3):

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

7- Apply the optimum decision variables ($X_{v,t,i}$ and $X_{f,t,i}$) for time step $t$ on the hydraulic simulator for the WDS which needs to be optimized.

8- Retrieve VSPs flow $Q_{v,t,i}^{Actual\ Speed,\ \ Simulator}$ and FSPs flow $Q_{f,t,i}^{Simulator}$ from the hydraulic simulator.
Using affinity laws, find VSPs flow at maximum speed $Q_{v,t,i}^{Maximum\ Speed,\ \ Simulator}$.

9- For all running VSPs during current time step $t$, if percentage difference between $Q_{v,t,i}^{Maximum\ Speed,\ \ Simulator}$ (which was found in the previous solution step 8) and $Q_{v,t,i}^{Maximum\ Speed}$ (used in Eq. (8) to calculate $P_{v,t,i}^{Maximum\ Speed}$ for the current iteration $i$) is less than 1%, then go to solution step 12. The 1% tolerance was selected after a limited sensitivity analysis on 3 case studies (see Chapter 4). These case studies have different topographies, demand patterns, characteristics for pumps and pipes. This threshold value results in convergence in the three case studies. In contrast, if a smaller tolerance value is used, then the number of iterations and computation time 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 1% tolerance may have to be adjusted for other different case studies.

10- If percentage difference between $Q_{v,t,i}^{Maximum\,Speed,\ \ Simulator}$ and $Q_{v,t,i}^{Maximum\,Speed}$ for one of the running VSPs (denoted by $v^*$) is more than 1%, then substitute $Q_{v,t,i}^{Maximum\,Speed}$ with $Q_{v,t,i}^{Maximum\,Speed,\ \ Simulator}$ in Eqs. (8), (15), and (18) for pump $v^*$ and for all other running pumps that are in parallel or in series with pump $v^*$ during the current time step $t$.

11- For all VSPs that change their $Q_{v,t,i}^{Maximum\,Speed}$ values in the previous solution step 10, update their head and efficiency values using their pump characteristics curves. Update their $P_{v,t,i}^{Maximum\,Speed}$ value using Eq. (8).

 Move to step 13.

12- For all running FSPs during current time step $t$, if percentage difference between $Q_{f,t,i}^{Simulator}$ (which was found in solution step 8) and $Q_{f,t,i}$ (which were used in Eq. (11) to calculate pump power $P_{f,t,i}$ for the current iteration $i$) is less than the 1% tolerance, and if $t$ is not the last time step, then set time step index $t = t + 1$ and go back to solution step 7. Do not start new iteration.

 If $t$ is the last time step, then go to solution step 17.

13- If percentage difference between $Q_{f,t,i}^{Simulator}$ and $Q_{f,t,i}$ for one of the running FSPs (denoted by $f^*$) is more than 1%, then substitute $Q_{f,t,i}$ with $Q_{f,t,i}^{Simulator}$ in Eqs. (11), (15), and (18) for pump $f^*$ and for all other running pumps that are in parallel or in series with pump $f^*$ during the current time step $t$.

14- For all FSPs that change their $Q_{f,t,i}$ values in the previous solution step 13, update their head and efficiency values using their pump characteristics curves.

    Update their $P_{f,t,i}$ value using Eq. (11).

15- Find the optimum decision variables ($X_{v,t,i}$ and $X_{f,t,i}$) for all pumps during all time steps and find the minimum deviation variables ($PEC_i$, $PVC_{a,t,i}$, and $NVC_{a,t,i}$) using GP, where Eq. (1) is the objective function and Eqs. (2), (3), (4), (5), (6), (7), (9), (10), (12), (13), (14), (15), (16), (17), (18) are the constraints.
16- Start new iteration $i = i + 1$ and go back to solution step 6.
17- If $t$ is the last time step $t = T$, then iteration will terminate and the solution obtained in solution step 15 is the optimum solution.
18- Find chlorine and water age at each demand node by running water quality simulation. Note that initial values of chlorine and water age will affect their final values.
19- Use Eq. (19) to calculate the weighted average chlorine or water age at demand nodes.

As it can be seen from above, each pump during each time step is assumed to have constant flow, head, efficiency, and eventually energy consumption and cost. The energy cost for each pump during each time step is multiplied by a decision variable which is the fraction of time step during which a pump is running for FSPs and the speed for VSPs. The constant conditions for each pump during each time step may be corrected after each iteration to match the feedback from the hydraulic simulator and to reflect the changing demand and other conditions in the network.

A computer program is developed to solve PSP using iELGP. The program is written in *MATLAB R2011b* software. Since Goal Programming is a special case of Linear Programming, the program uses the MILP solver *lp_solve 5.5.2.0* (Berkelaar *et al.* 2016) to solve the optimisation problem. The program calls *EPANET 2.0.12* to solve the hydraulic and water quality equations.

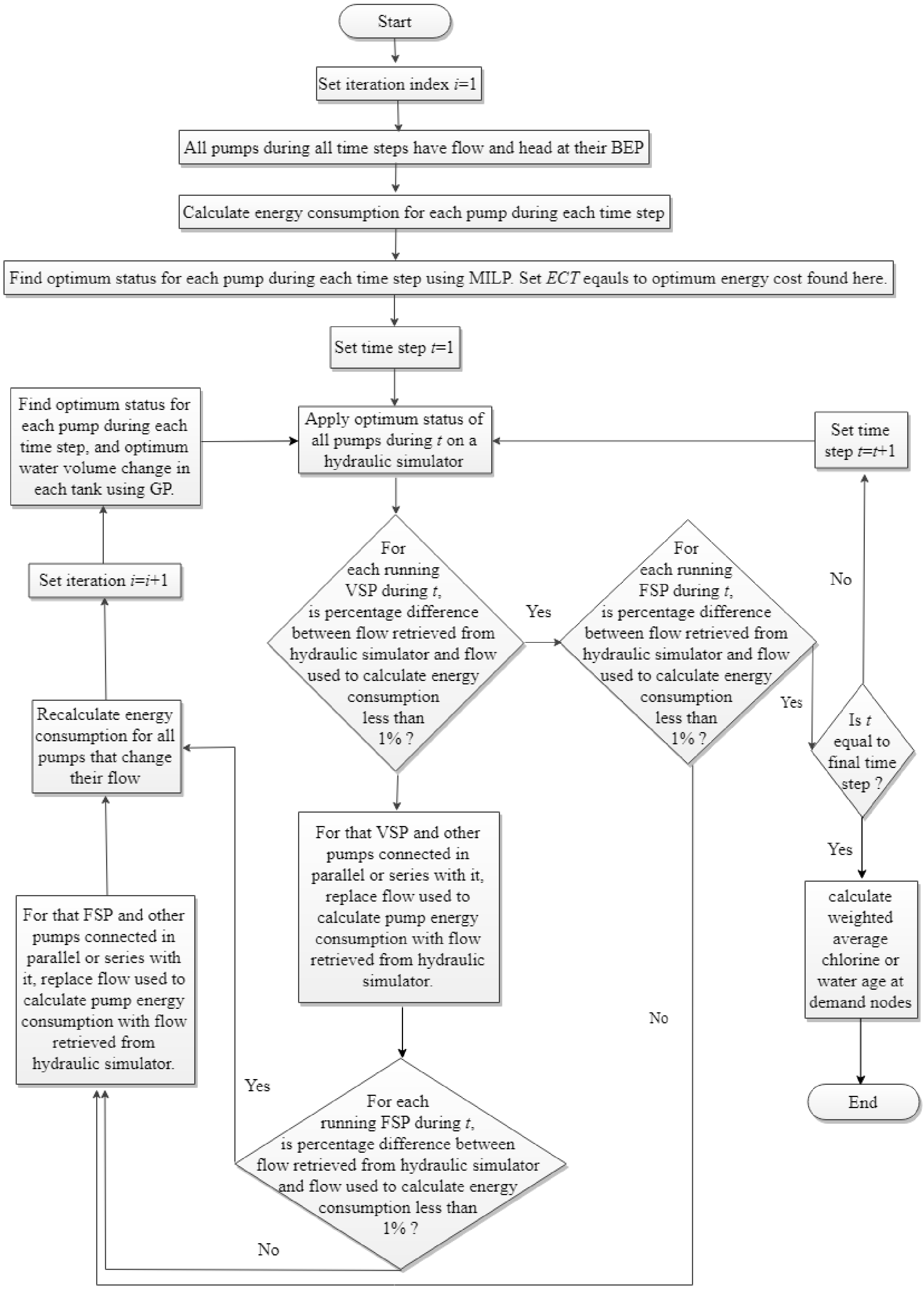


Figure 3. Flow chart for iELGP pump scheduling method

## 3.5 Summary

In this chapter, a new method for pump scheduling in water distribution systems is described in details. The method is named as iterative Extended Lexicographic Goal Programming (iELGP). The chapter starts by defining the pump scheduling problem as an optimisation problem with aim to minimise energy cost and water age. As in many scientific theories and methods, several assumptions are made to boost the computational efficiency without loss of accuracy. After that, the decision variables for VSPs and FSPs are defined and the mathematical equations that shape the optimisation problem (i.e. objective function and constraints) are formulated. Then, the solution steps are mentioned sequentially and presented in a flow chart.

The objectives of the optimisation that are set in section 1.3 in Chapter 1 are successfully attained in this chapter. The following Table *1* recalls these objectives and how they are addressed in the methodology presented in this chapter.

Table 1. Optimisation objectives and methodology

| **Optimisation objectives: to develop a pump scheduling method that** | **Objectives attainment methods** |
|---|---|
| 1- Minimises energy cost | Refer to Eq. (1), (2), (3) |
| 2- Improves water quality | Water quality is improved by minimising maximum water level in tanks or by minimising tanks inlet/outlet flow. Refer to assumption 8 and Eq. (1), (13), (19) for more details. |
| 3- Reduces maintenance cost | By increasing the length of the time steps which will eventually reduce the number of pump switches, because each pump is allowed to switch on once during a time step. |
| 4- Optimises the operation of | Refer to assumption 6 and Eq. (4), (5), |

| | |
|---|---|
| variable speed pumps. | (6), (7), (8). |
| 5- Can be applied on any type of WDS. | The formulation of the problem and the solution method are general and not tailored to specific shape/configuration of WDSs. |
| 6- In a computationally efficient manner | The PSP is carefully relaxed and linearised to boost the computational efficiency without loss of optimality. The high computational efficiency enable the method to be used for real-time control and to optimise the operation of large scale real-life WDSs. |

The effectiveness of solution methodology is tested on three different case studies as shown in the next chapter.

# Chapter 4: Case Studies

## 4.1 Introduction

The effectiveness of iELGP pump scheduling method developed in the previous chapter is tested, validated and demonstrated in this chapter on three different case studies. Each case study starts with the definition of pump scheduling objectives. This is followed by the description of a relevant WDS. At the end, results obtained are presented and discussed.

The WDSs in three case studies analysed here were optimised previously using pump scheduling methods other than the iELGP method. The results obtained using these other pump scheduling methods are compared with the results obtained using the iELGP method. This was done with the aim to evaluate the iELGP performance in comparison with existing pump scheduling methods.

## 4.2 Case Study I: Multi-tanks Artificial Network

### 4.2.1 Objective

The objective of this case study is to test the iELGP pump scheduling method on a water network with a simple layout. The objective of the pump scheduling is to minimise the energy cost only over a one week time horizon.

### 4.2.2 Problem description

The WDS in this case study is an artificial network that is shown in Figure 4. It was created by Price and Ostfeld (2012b) and used to test their iterative Linear Programming (iLP) pump scheduling method. The *EPANET* input file for the network is obtained from E. Price via personal communication (2016).

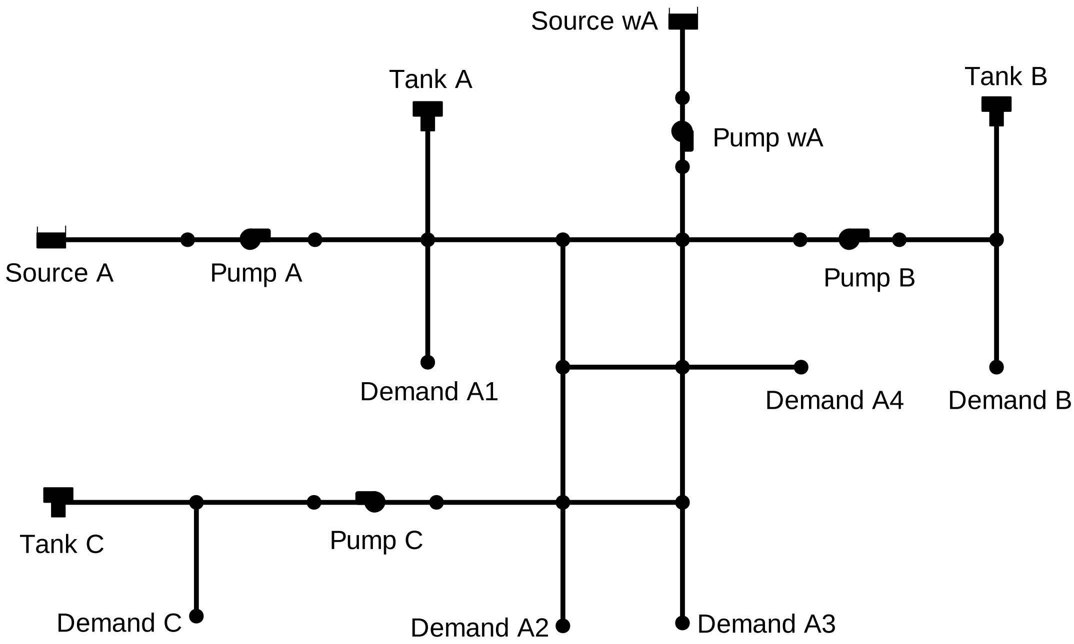


Figure 4. Artificial network (adapted from Price and Ostfeld 2012b)

The network consists of two water sources (Source A and Source wA), four pumps (Pump A, Pump wA, Pump B, and Pump C), three tanks (Tank A, Tank B, and Tank C), and six demand nodes (Demand A1, Demand A2, Demand A3, Demand A4, Demand B, Demand C). All pumps are fixed speed type and assumed to have fixed efficiency of 75%.

All pumps have single point characteristic curve. The flow and pressure at the single point is shown in Table 2.

Table 2. Pumps in Case I

| Pump | A | wA | B | C |
|---|---|---|---|---|
| Flow (m3/hr) | 1250 | 1000 | 400 | 250 |
| Pressure (m) | 47 | 99 | 101 | 55 |

All pipes have length of 1,000 m and roughness of 120 mm but they have different diameters ranging from 300 to 600 mm. The details for all tanks are shown in Table 3.

Table 3. Tanks in Case I

| Tank | A | B | C |
|---|---|---|---|
| Elevation (m) | 90 | 190 | 140 |
| Minimum level (m) | 0 | 0 | 0 |
| Maximum level (m) | 28 | 28 | 28 |
| Initial level (m) | 0 | 0 | 0 |
| Diameter (m) | 32 | 20 | 16 |

As can be seen in Table 3, the minimum water level in tanks is 0, but in reality it should not reach 0.

Although the network layout is simple, finding an optimal pump schedule for this network is still challenging because it has multiple sources, pumps, tanks, and demand nodes.

As mentioned, the objective in this case study is to minimise energy cost only. The scheduling time horizon is the average week of January with time step of 1 hour. Water demand occurs at all demand nodes only from 7:00 h to 17:00 h as shown in Figure *5*. The electricity tariffs are as follows:

- Low electricity tariff of 0.3051 New Israeli Shekel (NIS)/kWh during the following time periods:
    - Sunday to Thursday: 00:00 to 06:00, 08:00 to 16:00, and 22:00 to 24:00;
    - Friday: 00:00 to 16:00, and 20:00 to 24:00; and

- Saturday: 00:00 to 17:00, and 21:00 to 24:00.

- Moderate electricity tariff of 0.5347 NIS/kWh during the following time periods:
  - Sunday to Thursday: 06:00 to 08:00;
  - Friday: 16:00 to 20:00; and
  - Saturday: 19:00 to 21:00.
- High electricity tariff of 0.9125 NIS/kWh during the following time periods:
  - Sunday to Thursday: 16:00 to 22:00 hours
  - Saturday: 17:00 to 19:00 hours.

The energy cost target $ECT$ is calculated using solution steps 1-5 which are mentioned in section 3.4 of the thesis:

1- Iteration index ($i$) is set to 1.

2- This solution step is skipped because there is no variable speed pumps in Case I.

3- Since all pumps in Case I have single point characteristics curves and constant efficiency of 75%, the flow and pressure at the single point is used to calculate power of each pump. Using Eq. (11), power of pump A is 21.76 kW, pump wA is 36.67 kW, pump B is 14.96 kW, pump C is 5.09 kW.

4- Using linear programming, optimum energy cost and optimum decision variable for each pump during each time step is found.

5- The $ECT$ is set to the optimum energy cost found in previous step which is NIS 7,332.

The weight factor $w$ in Eq. (1) is set to 0 since improving water quality is not required in this example. Pump switches are not constrained in this case study.

### 4.2.3 Results and Discussion

Using iELGP pump scheduling method, the operation of the pumps in the above WDS is optimised. Figure 5 shows the optimum flow obtained for each pump over the scheduling time horizon. Figure 6 shows the optimum water level in each tank over the same time horizon.

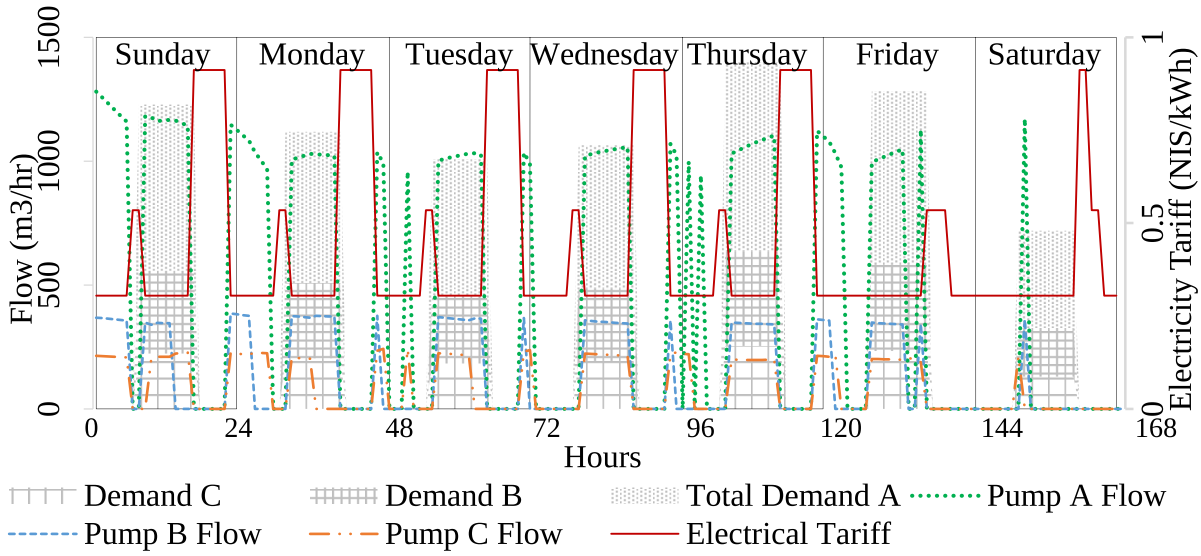


Figure 5. Optimum pumps flow

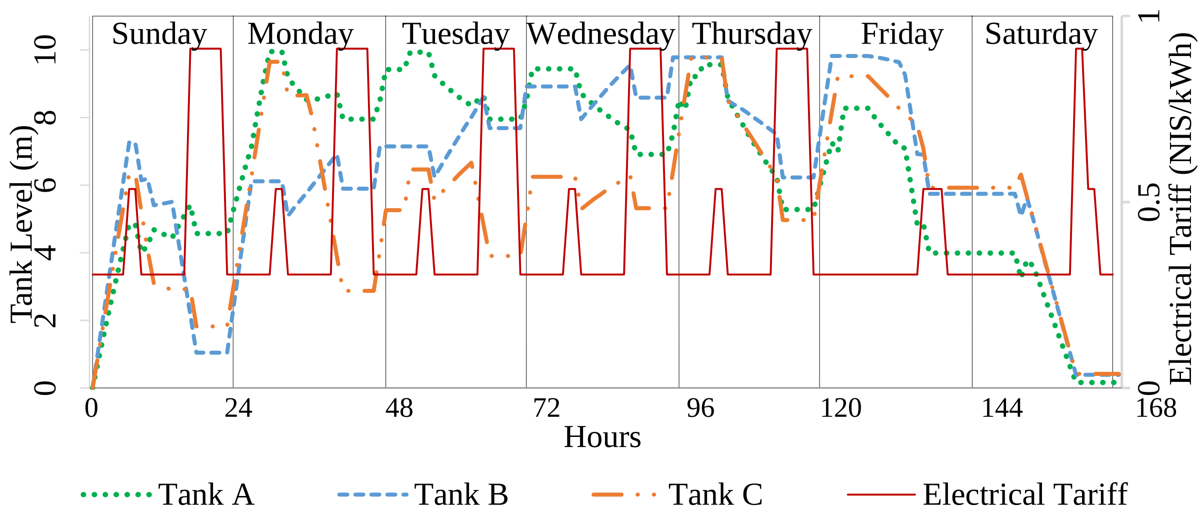


Figure 6. Optimum water levels in tanks.

As it can be seen from Figure 5, pumps are not running (i.e. have zero flow) during the moderate and high electricity tariff periods. Thus, water levels in tanks are decreasing during these time periods, as shown in Figure 6. Instead, pumps are running during low electricity tariff periods and hence water levels in tanks are increasing during these time periods. Pump wA is not running at all because it is more energy consuming (i.e. expensive) than pump A and is not required to provide the sufficient volume of water to meet the system demands.

Note that pressure in all six demand nodes is above 83 m all the time. It is above the minimum usually required pressure at demand nodes which is 20 m (Ghorbanian 2015).

The structure of the electricity tariff, the demand pattern, the size of tanks, and the size of pumps all affect the ability to reduce energy cost in WDSs through pump scheduling. In this case study, water demand is occurring mostly during the low electricity tariff period hence the optimum energy cost is likely to be higher if there is more water demand during moderate and high electricity tariffs.

The size of pump A and tank A helped to supply demand nodes A1-A4 and pumps B and C during low electricity tariff period without the need to start the energy expensive pump wA. Pumps were able to refill tanks during low electricity tariff periods. If pumps' sizes were smaller, then they would have taken longer time to refill tanks and they might had to run during moderate and high electricity tariff. Tanks were able to supply demand during moderate and high electricity tariff. If tanks' sizes were smaller, then would have emptied within short time, and pumps might had to run during moderate and high electricity tariff periods.

In light of the above, pump scheduling becomes useful tool in WDSs development. Pump scheduling can evaluate the savings in energy cost (relative current cost) if a pump size is changed or a new tank is constructed. In this case study, all pumps ran during low electricity tariff only. Thus, pump scheduling will not reduce energy cost further if pumps' sizes or tanks' sizes are increased.

Figure 7 shows the time series of water age in all six demand nodes in the network.

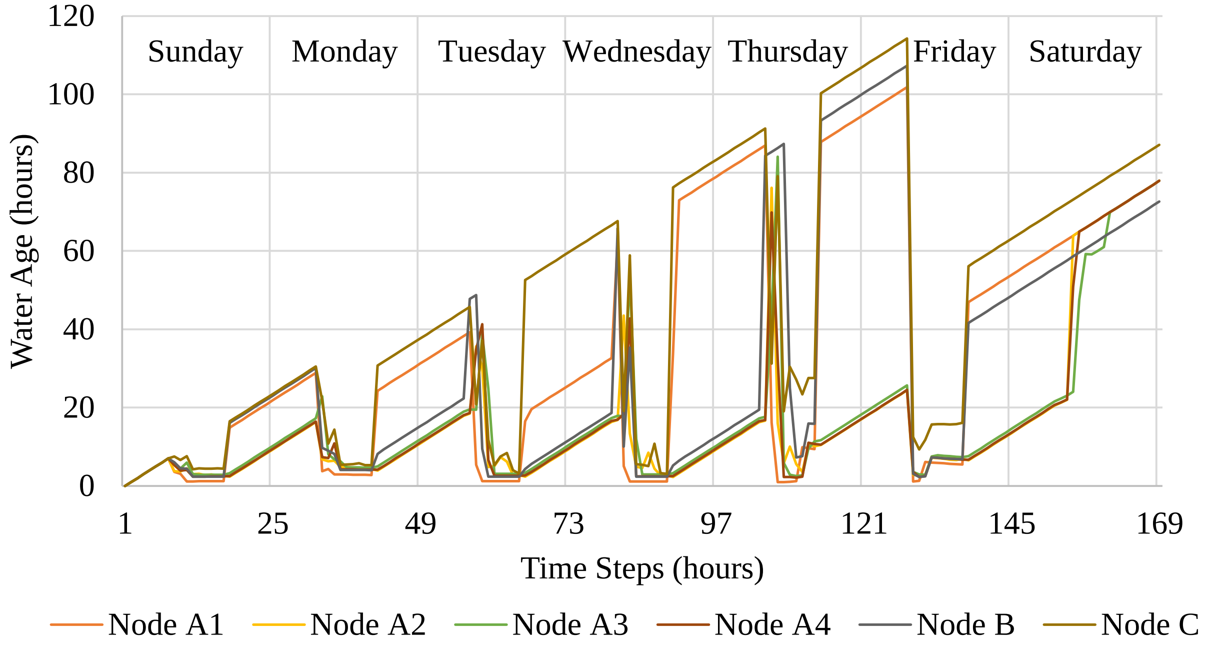


Figure 7. Time series for water age in all demand nodes.

Recall that demand hours during all days is from 7:00 to 17:00 hours. As shown in Figure 7, in the first six days water age increases during first demand hours (07:00 to 09:00 each day). Water age the drops from 09:00 to 17:00 hours. Maximum water age value in each day is increasing because water levels in tanks are kept at high level as shown in Figure 6.

In the last day, pumps run for few hours as shown in Figure 5. Thus, water levels in all tanks decreases till they reach their initial water levels as shown in Figure 6. Demand nodes are supplied from tanks (not from source fresh water) most of the time to minimize energy cost. Due to that, water age in all demand nodes is high in the last day.

The water age shown in Figure 7 is expected to repeat in the next week, because tanks final water levels reach initial levels. Water age in Case I can be improved by stopping pumps for some time during low electrical tariff to allow water levels inside tanks to drop and refresh. However, this will increase the energy cost.

Table 4 compares the results obtained using the iLP and iELGP pump scheduling methods. Note that both methods are applied to the same network shown in Figure 4 and using the same initial conditions and constraints.

Table 4. Comparison between results from iLP, iELGP pump scheduling methods (better performance values bolded and underlined)

| | iLP | iELGP |
|---|---|---|
| **Energy Cost for Average Week of January (NIS)** | 10,895 (E. Price, Personal communication, 2016) | **<u>7,857.01</u>** |
| **Computational Time (min)** | **<u>1.17</u>** | 2.15 |
| **Number of Pump Switches:** | | |
| **Total** | **<u>37</u>** | 45 |
| **Pump A** | 13 | 17 |
| **Pump wA** | 0 | 0 |
| **Pump B** | 12 | 14 |
| **Pump C** | 12 | 14 |
| **Computer:** | | |
| **Processor Speed (GHz)** | 1.80 | 2.10 |
| **RAM (GB)** | 1.0 | 8.0 |

The energy cost of optimum pump schedule obtained from iELGP method is NIS7,979 which is 28% less than the schedule obtained using the iLP method. The computation time for iELGP is higher than the computation time of the iLP although iELGP runs on faster computer. Having said this, both computational times are very low and would allow using both methods for real-time pump scheduling. The optimum pump schedule obtained using the iELGP method has slightly higher number of pump switches than the one obtained using the iLP method (note that the number of pump switches was not constrained during the optimization in either of the two methods). This is a rather small price to pay for substantial cost savings achieved.

The number of iterations and computation time in iELGP can be reduced by setting the energy cost target $ECT$ to a more realistic value. Instead of assuming that pumps run at their BEP as mentioned in section 3.4 in chapter 3, the actual operating flow range for each pump can be determined pre-optimisation and the flow that has the highest efficiency within that range can be chosen to calculate the energy cost target $ECT$. In this case, the achieved energy cost $AEC$ will be closer to the energy cost target $ECT$ and the number of iterations and computational time will be reduced.

In each iteration, *EPANET* re-initialises the hydraulic simulation starting from the initial time step. The computation time can be reduced significantly if *EPANET* re-initialises the simulation directly to the wanted time step. This was done in Price and Ostfeld (2016a) and in case study III in this thesis.

Enforcing tanks to recover their initial water levels (Eq. (17) in Chapter 3) is necessary for having sustainable operation in the longer run. However, recovering the initial water level in tanks increases the energy cost. To reduce that increase in energy cost, the optimisation time horizon should be long (e.g. 1 week as in this case study). In this case, tanks should recover their initial water level only once (at the end of the week). However, if pumps are optimised day by day, then tanks' are required to recover their initial water level every day, which will increase the energy cost.

Water demand and electricity tariff are the two main variables that shape the optimum pump schedules. To test the performance of iELGP method and to study the effect of time step length on results, the time step length (1 hour in the original Case I) is changed as per the following 3 options.

- First option: length of time step is equal to maximum duration of time during which water demand is constant.
- Second option: length of time step is equal to maximum duration of time during which electricity tariff is constant
- Third option: length of time step is equal to maximum duration of time during which water demand and electricity tariff are constant.

Pump scheduling method iELGP is tested in each option and results are compared as shown in Table 5.

Table 5. Comparison between original Case I and three different options for time step length.

| | Original Case | First Option | Second Option | Third Option |
|---|---|---|---|---|
| **Length of time step** | 1 hour | Equal to maximum duration of time during which water demand is constant. | Equal to maximum duration of time during which electricity tariff is constant | Equal to maximum duration of time during which water demand and electricity tariff are constant |
| **Number of time steps** | 168 | 7 | 26 | 39 |
| **Energy Cost for Average Week of January (NIS) using iELGP pump scheduling method** | **7,857.01** | 8,310.19 | 8149.89 | 7977.76 |
| **Number of pump switches:** | | | | |
| **Total** | 45 | **21** | 28 | 34 |
| **Pump A** | 17 | 7 | 10 | 12 |
| **Pump wA** | 0 | 0 | 0 | 0 |
| **Pump B** | 14 | 7 | 9 | 11 |
| **Pump C** | 14 | 7 | 9 | 11 |
| **Weighted average water age (hours)** | 54.98 | **47.43** | 65.20 | 57.69 |
| **Computational time (min)** | 2.15 | **0.70** | 1.11 | 1.63 |

As can be seen from Table 5, the first option has the highest energy cost because pumps are allowed to switch on/off for 7 times only during the whole optimisation period. However, the limited number of time steps reduces the total number of pump switches to 21, because pumps are allowed to switch on once in the beginning of time step (as mentioned in second assumption in section 3.2 of this thesis). Additionally, the first option has the lowest weighted average water age, because pumps are allowed to start when there is change demand only. Thus, fresh water is supplied to demand nodes. The first option has the lowest computational time because it has lowest number of time steps, which means lowest number of decision variables.

The original Case I has the lowest energy cost because it has the highest number of time steps, thus pumps have more flexibility to start and stop. The second option has the highest water age because pumps are allowed to start when there is change in electricity tariff only regardless of water demand.

## 4.3 Case Study II: Richmond Network

### 4.3.1 Objective

The objective of this case study is to test the iELGP pump scheduling method on a larger, real water network. The objective of pump scheduling is to minimise energy cost only whilst limiting the maximum number of pump switches over a 24 hour scheduling horizon.

### 4.3.2 Problem description

The WDS in this case study is the Richmond network. It is a real water network that exist in London, United Kingdom. The *EPANET* input file of Richmond network that is optimised in this case study is available in Lopez-Ibanez (2016). The skeletonized Richmond network is shown in Figure 8. The full version of the network which is available in in Lopez-Ibanez (2016) was used in the optimisation.

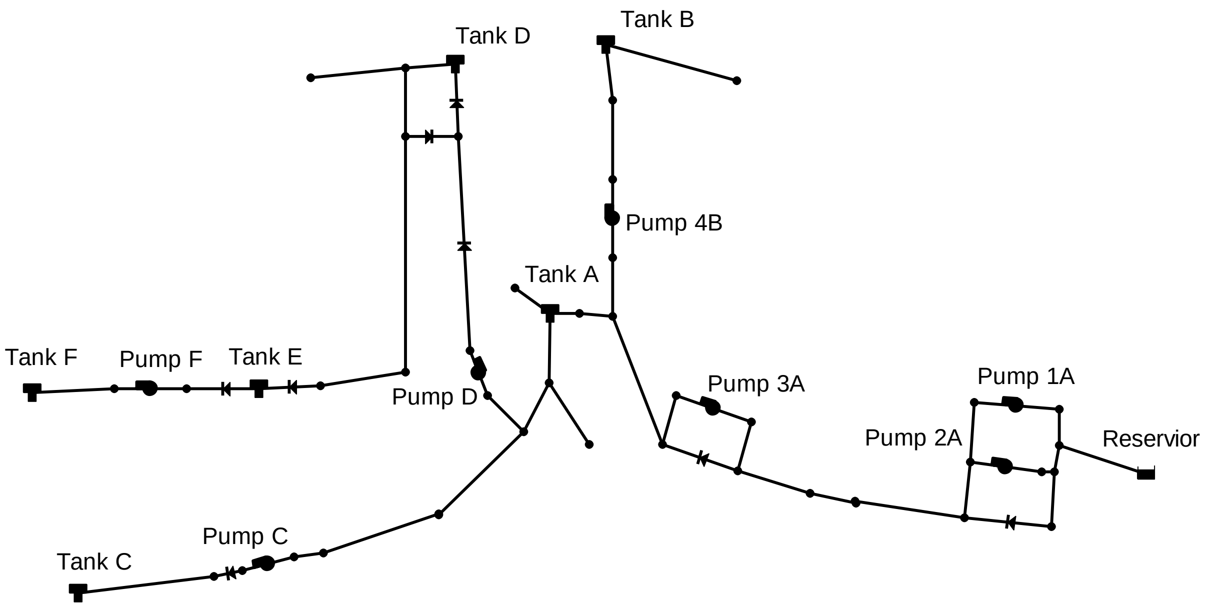


Figure 8. Skeletonized Richmond network (adapted from Center for Water Systems 2001)

Richmond water network consists of a single water source, 7 fixed speed pumps (1A, 2A, 3A, 4B, C, D, F), 6 tanks (A, B, C, D, E, F), 948 pipes and 836 nodes. The details for all tanks are shown in Table 6.

Table 6. Tanks in Case II

| Tank | A | B | C | D | E | F |
|---|---|---|---|---|---|---|
| Elevation (m) | 184.13 | 216 | 258.9 | 241.18 | 203.01 | 235.71 |
| Minimum level (m) | 0 | 0 | 0 | 0 | 0 | 0 |
| Maximum level (m) | 3.37 | 3.65 | 2 | 2.11 | 2.69 | 2.19 |
| Initial level (m) | 3.2 | 3.4675 | 1.9 | 2.0045 | 2.5555 | 2.0805 |
| Diameter (m) | 23.5 | 15.4 | 6.6 | 11.8 | 8 | 3.6 |

All pumps have multi-point characteristic curves as shown in Figure 9.

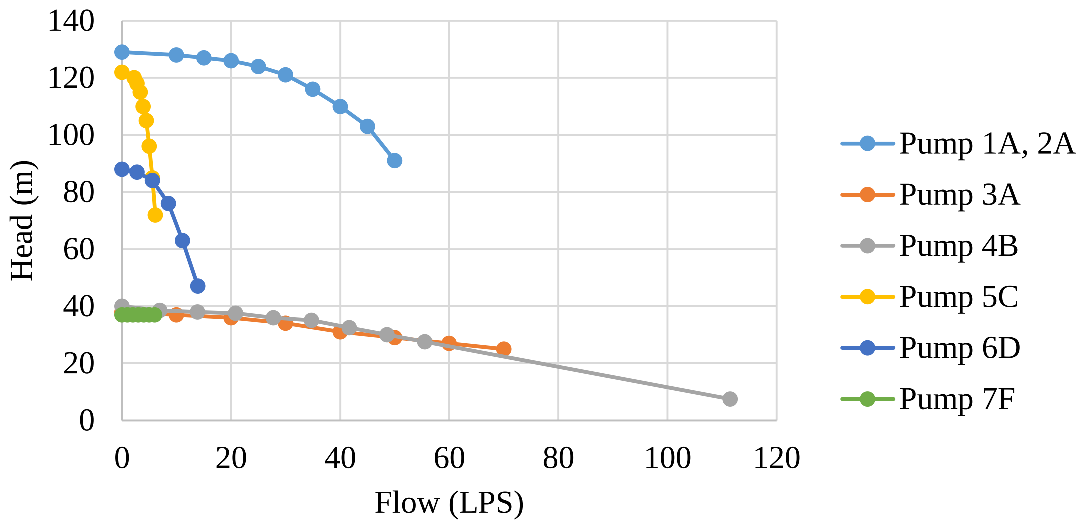


Figure 9. Case II pumps' characteristics curves.

All pumps have multi-point efficiency curves as shown in Figure 10.

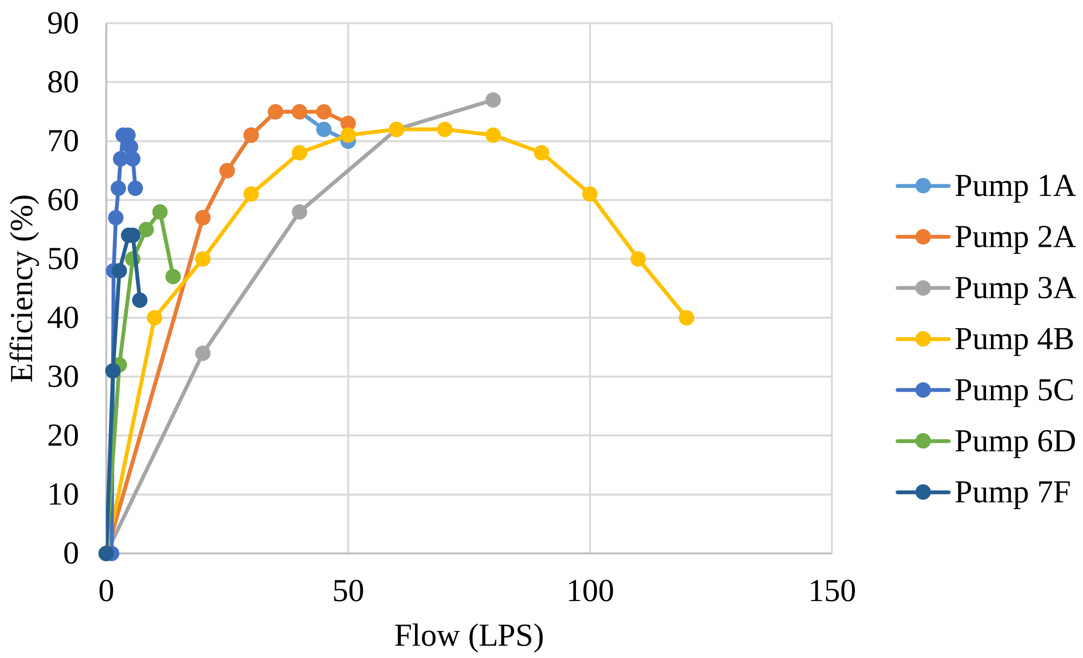


Figure 10. Case II pumps' efficiency curves.

The objective in this case study is to minimise energy cost only. The scheduling horizon is 24 hours starting at 7:00 in the morning. All tanks have initial water level equal to 95% of the maximum water level (Lopez-Ibanez 2016). The minimum water level in all tanks is 0 (in reality water level in tanks should not reach 0). There are two electricity tariff periods: the low electricity tariff period is from 00:00 to 7:00 and the high electricity tariff period is from 07:00 to 00:00. Water demand is continuous during all the time in all demand nodes.

Energy cost target $ECT$ is set to £70 using the method described in section 3.4 of chapter 3. The weight factor $w$ in Eq. (1) is set to 0 since improving water quality is not required in this case study. Pump switches are constrained in this case study implicitly by increasing the length of time steps and allowing pumps to start once during each time step. The maximum number of pump switches in this case study is set to 3. Thus, the optimisation time horizon is divided into 3 time steps. The first time step is from 07:00 to 15:00 and the second time step is from 16:00 to 23:00. The electricity tariff during the first and the second time steps is high. The third time step is from 00:00 to 07:00 during which electricity tariff is low. As can be seen, the small number of time steps was chosen to limit the number of pump switches whilst accounting for different electricity tariff periods.

### 4.3.3 Results

Using iELGP pump scheduling method, the operation of the pumps is optimised. The energy cost of optimum pump schedule obtained from iELGP method is £85.69. The iELGP method makes 34 iterations before obtaining that optimum pump schedule

Figure 11 shows the optimum pump schedule while Figure 12 shows the optimum water level in each tank over the scheduling time horizon.

| | First Time Step | | | | | | | | | Second Time Step | | | | | | | | Third Time Step | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Pumps | 07:00 | 08:00 | 09:00 | 10:00 | 11:00 | 12:00 | 13:00 | 14:00 | 15:00 | 16:00 | 17:00 | 18:00 | 19:00 | 20:00 | 21:00 | 22:00 | 23:00 | 00:00 | 01:00 | 02:00 | 03:00 | 04:00 | 05:00 | 06:00 |
| 1A | | | | | | | | | | | | | | | | | | | | | | | | |
| 2A | | | | | | | | | | | | | | | | | | | | | | | | |
| 3A | | | | | | | | | | | | | | | 42 | | | | | | | | | |
| 4B | | | | | | | | | | | | | 12 | | | | | | | | | | | 42 |
| C | | | | | | | | | | | 6 | | | | | | | | | | | 30 | | |
| D | | | | | | | | | | | | | | | | | | | | | | | | |
| F | | | | | | | | | | | | | | | | | | | | 6 | | | | |

Figure 11. Optimum pump schedule for Richmond network

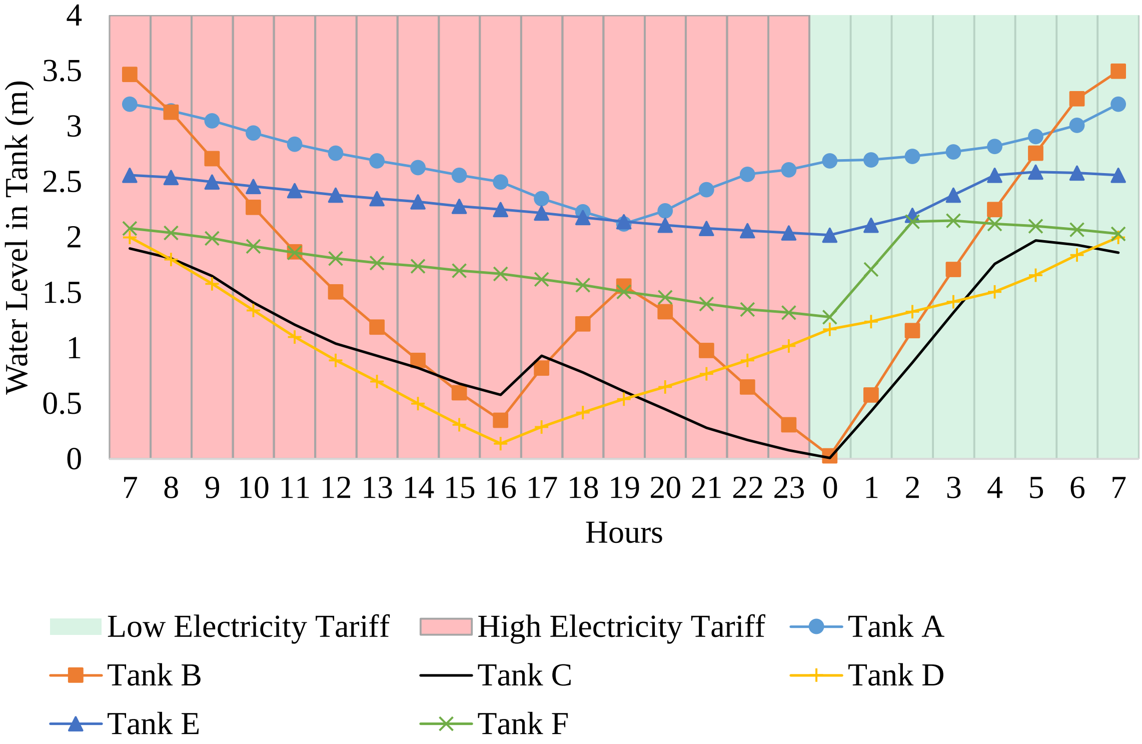


Figure 12. Optimum water levels in Richmond network tanks

White cells in Figure 11 mean pumps are not working during the corresponding hour. Grey cells in the same figure mean pumps are working during corresponding hour. If there is a number inside a grey cell, it indicates the number of minutes after which the pump is stopped.

As it can be seen from Figure 11, during the first time step, all pumps are not running because electricity tariff is high and tanks have sufficient water to supply the demand nodes. As a consequence, at the end of the first time step, water level in tanks B, C, and D are low. Thus, pumps 1A, 3A, 4B, C and D are started in the second period and they run for the minimum required time because electricity tariff is high during that time step. During the third time step, all pumps are running most of the time to recover the initial water level in the tanks during this low electricity tariff period.

As can be seen from Figure 12, water levels in tanks are decreasing during the high electricity tariff period because pumps are not running. During the low electricity tariff period, water levels in tanks are in increasing because pumps are running. Final water level in all tanks is at least equal to their initial water level, according to Eq. (17) in chapter 3.

Average pressure in all demand nodes is above 50 m all the time except demand nodes which are mentioned in the following Table 7.

Table 7. Demand node in Case II with pressure less than 20 m.

| Demand node ID | Average pressure (m) | Time | Reason | Is low pressure due to optimum pump schedule? |
|---|---|---|---|---|
| **20, 31, 42, 64, 86, 97, 109** | 6.6 | Between 07:00 and 16:00 | These demand nodes can be supplied by gravity from the source or by pumps 1A and 2A. Between 07:00 and 16:00, these demand nodes were supplied by gravity and pumps 1A and 2A were off to reduce energy cost. | Yes |

| | | | | |
|---|---|---|---|---|
| **405, 460, 540** | 16 | All the time | These demand nodes are be supplied by gravity only from tank B. These demand nodes suffer from low pressure even if water level in tank B is kept at maximum. Pump scheduling has nothing to do with this problem. | No |
| **686** | 18.2 | Most of the time | This demand node is supplied by gravity from tank C or by pump C. Water level in tank C should be always kept near maximum to avoid low pressure in this demand node. | Yes |
| **281, 282, 283, 286, 287** | 17.7 | Between 07:00 and 16:00 | These demand nodes can be supplied by gravity from tank D or by pumps D. Between 07:00 and 16:00, these demand nodes were supplied by gravity and pump D were off to reduce energy cost. | Yes |
| **301, 302, 304, 306, 308, 310** | 14.1 | All the time | These demand nodes can be supplied by gravity from tank D or by pumps D. These demand nodes suffer from low pressure even if water level in tank D is kept at maximum and pump D is running. Pump scheduling has nothing to do with this problem. | No |

In this case study, the optimisation time horizon is 1 day. Water quality analysis is usually made over long time (1 week) to ensure having periodical behavior of water quality parameters. Due to that, the optimum pump schedule and the demand patterns in Case II is repeated for 6 more days (total optimization time horizon 1 week).

After running 1 week (168 hours) water quality simulation, it is found that demand nodes ID 741, 742, 743, 744, 756, 757, 760 have average water age of 148 hours at the end of the week (see Figure 13). These nodes are farthest away from the water source. Nodes ID 741, 742, 743, 744 are supplied from tank E. Nodes ID 756, 757, 760 are supplied from pump F or tank F.

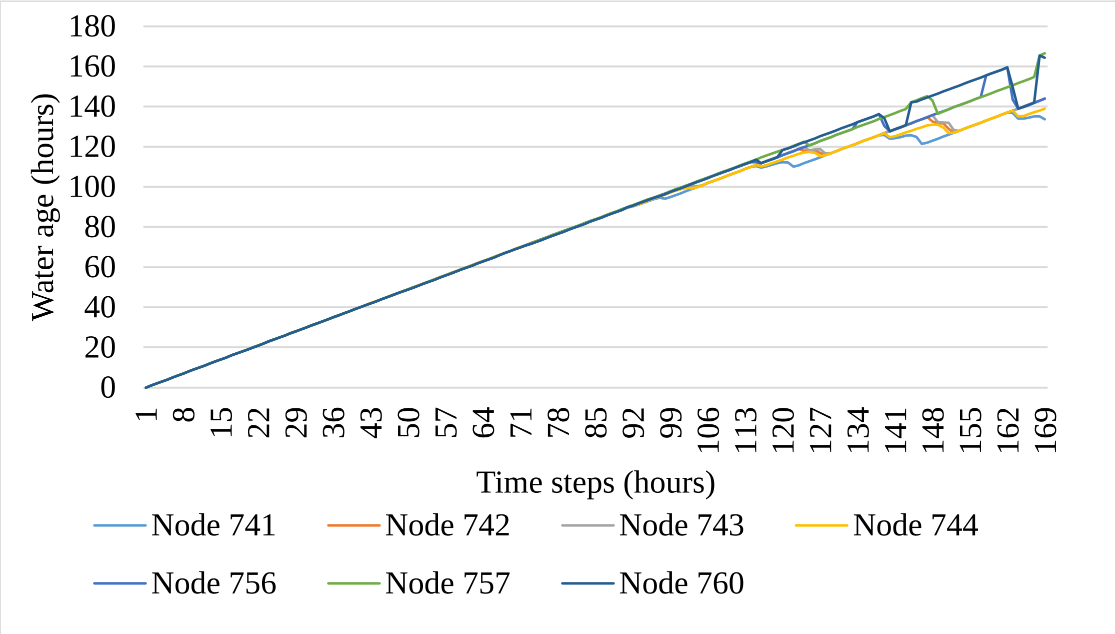


Figure 13. Time series for water age in some demand nodes.

To reduce water age in demand nodes ID 741, 742, 743, 744, the maximum water level of tank E should be reduced because these demand nodes have very low demand relative to tank E capacity. The total daily demand in these nodes is 32 m3 and the initial water volume (95% of the maximum) in tank E is 128.5 m3.

To reduce water age in demand nodes ID 756, 757, 760, pump F should run intermittently regardless of electricity tariff to avoid storing water in tank E and F for long time.

The average water age for all other demand nodes (440 nodes) is 22 hours.

As shown in Figure 12, water level in tank A stays at high level because tank A (and all other tanks) is required to recover its initial water level before the end of the optimisation period. The capacity of pumps 1A, 2A, 3A which supply the whole network (in addition to tank A) is relatively small. Thus, if water level in tank A is allowed to drop, then these pumps will not be able to recover the initial water level of tank A.

Figure 14 shows the time series for water age in tanks A and E. The high water level in tank A didn't deteriorate its water age. This is because tank A has high inlet/outlet flow rate.

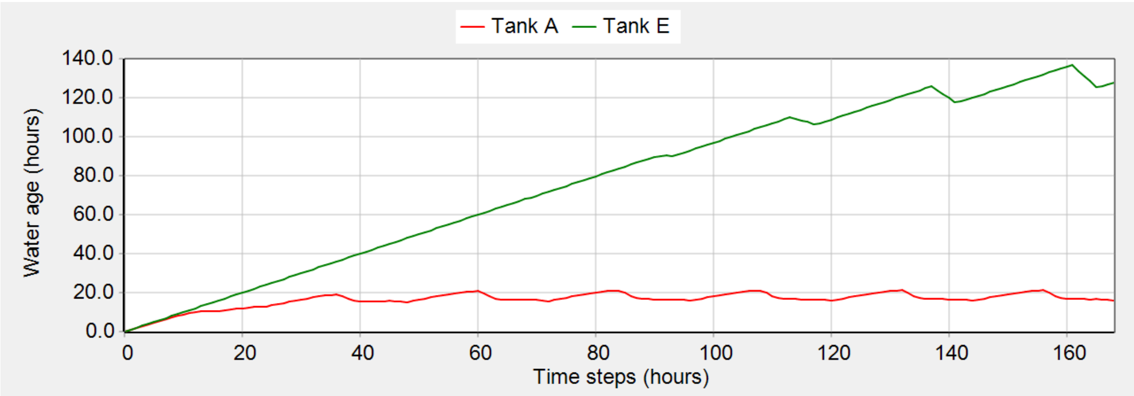


Figure 14. Time series for water age in tanks A and E

As shown in Figure 12, water level in tank E stays at high level because (as mentioned previously) tank E has low demand compared to its capacity. Figure 14 shows that water inside tanke E has high water age. The high water age in tank E causes high water age in demand nodes ID 741, 742, 743, 744, 756, 757, 760 as mentioned previously. To reduce water age in tank E, maximum water level in tank E should be reduced and pump F which draws water from tank E should run intermittently regardless of electricity tariff.

Table 8 compares results from Hybrid Genetic Algorithms (van Zyl et al. 2004), Ant Colony Optimisation (Lopez Ibanez et al. 2008), and iELGP pump scheduling methods. All these methods are applied on the same Richmond network for the same initial conditions and constraints.

Table 8. Comparison between results from HGA, ACO, iELGP pump scheduling methods (best results shown in bolded text)

| Optimization Method | HGA (van Zyl, et al. 2004) | ACO (López-Ibáñez, et al. 2008) | iELGP |
|---|---|---|---|
| **Energy Cost (£/day)** | 96.70 | 100.55 | **85.69** |
| **Computation Time** | 1.1 hours | 2.46 hours | **4 seconds** |
| **Number of Pump Switches** | Constrained but not available (results not mentioned in the paper) | 12 pump switches | **10 pump switches** (Pump 1A: 1, Pump 2A: 1, Pump 3A: 2, Pump 4B: 2, Pump 5C: 2, Pump 6D: 1, Pump 7F: 1) |
| **Computer:**<br>**Processor Model**<br>**Processor Speed (GHz)** | Pentium<br>0.40 | Pentium 4<br>3.20 | Intel® Core™ i7-3612QM<br>2.10 |

As can be seen from Table 8, the iELGP pump scheduling method gives substantially lower energy cost than HGA and ACO pump scheduling methods. In addition, iELGP gives optimum pump schedule within very short time of 4 seconds, even when allowing for the slower computers used by HGA and ACO pump scheduling methods. The optimum pump schedule obtained from iELGP has lower number of pump switches than the one obtained from ACO.

### 4.3.4 Discussion

Based on the results shown in the previous section, the following observations / discussions are made here:

- HGA and ACO have parameters that need to be tuned before they run, like number of ants in ACO and probability of crossover in HGA. However, the iELGP pump scheduling method does not have parameters that need to be tuned.

- HGA and ACO are stochastic optimisation methods that need to be run several times to ensure obtaining optimal solution. However, the iELGP is a deterministic optimisation method that gives the same optimal solution every time it runs.
- Unlike other existing pump scheduling methods that assume fixed efficiency for pumps (Coulbeck and Chen 1991; Ostfeld and Salomons 2004a), iELGP is able to handle the variable efficiency of the pumps. As mentioned in solution steps 11 and 14 in Section 3.4 of Chapter 3, iELGP updates pumps' efficiency after each iteration. True pump efficiency is required for accurate calculation of pump's power (see Eq. (8) and (11) in Chapter 3). Thus, iELGP gives more realistic optimal energy cost than the other two methods. Optimisation methods HGA and ACO in Table *8* did also use variable efficiency for pumps.
- Pump C run for some time during the high electricity tariff and didn't run during the whole low tariff period. If tank C is bigger, then pump C will switch one time only during the low electricity tariff and will not run during the high electricity tariff. Thus, energy cost and maintenance cost of pump C will be further reduced. Before deciding to make new investment and increase the size of tank C, we should check capital cost, interest rate, payback period to ensure that the investment is worthy.
- The consequences of constraining pump switches implicitly (by increasing the length of time steps and allowing each pump to switch once during each time step) is as follows:
    - Maximum number of pump switches for all pumps will be the same, and equals to the number of time steps (in this case study it is 3). Thus, this method may not be suitable if maximum number of pump switches for one pump is required to be different than the other pumps.
    - The maximum number of pump switches for all pumps is dependent on the number of electricity tariffs during the optimisation time horizon. This is because the electricity tariff during each time step should be constant. If there are 3 different electricity tariffs during the optimisation time horizon, then the number of time steps and the maximum number of pump switches for all pumps cannot be less than 3.

- During each time step, average demand for each node and flow for each pump are used in calculations. They are equal to the summation of hourly demand or hourly pump flow during that time step divided by the length of that time step. This may cause water levels in tanks to exceed maximum/minimum limits for part of the time step, especially if the time step is long.
- A solution may not exist if there is a big pump that supplies water to a small tank and the time steps are long. This is because this pump might need to start and stop frequently. However, the number of time steps is reduced and each pump is allowed to switch once at the beginning of the time step.

- The computational time for iELGP method in this case study (4 seconds) is less than the computation time for iELGP method in case study I (2.15 minutes), although the network size in this case study is larger than that in case study I. Additionally, the number of iterations in this case study is 34 while number of iterations in case study I is 1,477. These differences exist because the optimisation time horizon in this case study is 1 day and the number of time steps is 3, while the optimisation time horizon in case study I is 1 week and the number of time steps is 168. The more time steps means more pump flow values ($Q_{f,t,i}$ in Eq. (11) in chapter 3) that need to be corrected leading to increased number of iterations and larger computational time.
- The decision variable $X_{f,t,i}$ for FSP in the iELGP method represents the fraction of time step during which pump is running. This is not a binary decision variable, it is a real variable that can have a value of 0 or 1 or any value between 0 and 1, as mentioned in Eq. (10) in chapter 3. Having real decision variables for pumps leads to the following two advantages:
  - It reduces the computational time for iELGP pump scheduling method. Optimisation methods that have binary or integer decision variables require more computation time because additional method like branch and bond need to be used.
  - It increases the optimality of the solutions, because pumps are allowed to run for a fraction of a time step.

Having said this there are downsides to using mixed integer values. Using these decision variables in the iELGP method may cause incorrect calculations when there are two or more pumps connected in parallel (e.g. pumps 1A and 2A in case II) or in series (e.g. pumps A and B in case I). This is because if the two pumps connected in parallel or series are on at the beginning of a time step, and one of them stopped sometime during the time step, then the flow of the other pump which is still running will change. However, the iELGP method retrieves the flow of pumps from the hydraulic simulator at the beginning of the time step only (see solution step 8 in section 3.4 of chapter 3). In this case study the optimisation model will have few inaccurate pump flow values $Q_{f,t,i}$. The consequence of this problem is that calculation of energy cost might be inaccurate. Water level in an associated tank might exceed its minimum/maximum limits. Additionally, Final water level in an associated tank might be smaller or larger than its initial water level. Two solutions are used to solve this issue:

- To retrieve the flow for the pump (that remains running in the previous example) twice, at the beginning of the time step and when the other pump stops. Then, each flow value should be multiplied by its fraction from the time step. Both flow values should be summed and used in the optimisation. This improvement was used in case study III in this thesis.
- Another possible solution is to decrease the length of time steps ($L_t$ in Eq. (3) in section 3.3 in chapter 3). This will reduce the time during which the pump (that remains running in the previous example) has incorrect flow value. Thus, the feasibility and optimality of the solution will increase but at the expense of computational time. This improvement was not tested.

## 4.4 Case Study III: C-Town Network

### 4.4.1 Objective

The objective of this case study is to test the iELGP pump scheduling method on another real WDS (C-town) that has different topography than the Richmond network. The objective of the scheduling is to minimise the energy cost whilst achieving the minimum chlorine concentration of 0.28 mg/l at all demand nodes. Three case are analysed here: Case A, Case B, and Case C.

In Case A, all pumps have constant speed and the minimum required chlorine concentration is achieved by reducing tanks' maximum water levels. This case was optimised previously in Price and Ostfeld (2016) using graph theory. The same case is optimised here using the iELGP pump scheduling method. Results obtained by Price and Ostfeld (2016) are compared with the results obtained by using the iELGP method.

In Case B, all pumps have constant speed and the minimum required chlorine concentration is achieved by minimising tanks inlet/outlet flow rates. Results from Case B are compared with results from Case A to see which approach for achieving minimum chlorine performs better.

In Case C, some pumps have variable speed and the minimum required chlorine concentration is achieved by minimising tanks inlet/outlet flow rates. Results from Case C are compared with results from Case B to see how variable speed pumps affect the optimisation results.

### 4.4.2 Problem description

C-town is a real water distribution network. The *EPANET* input file of C-town network that is optimised in this case study is available in WDSA (2014) and is shown in Figure *15*.

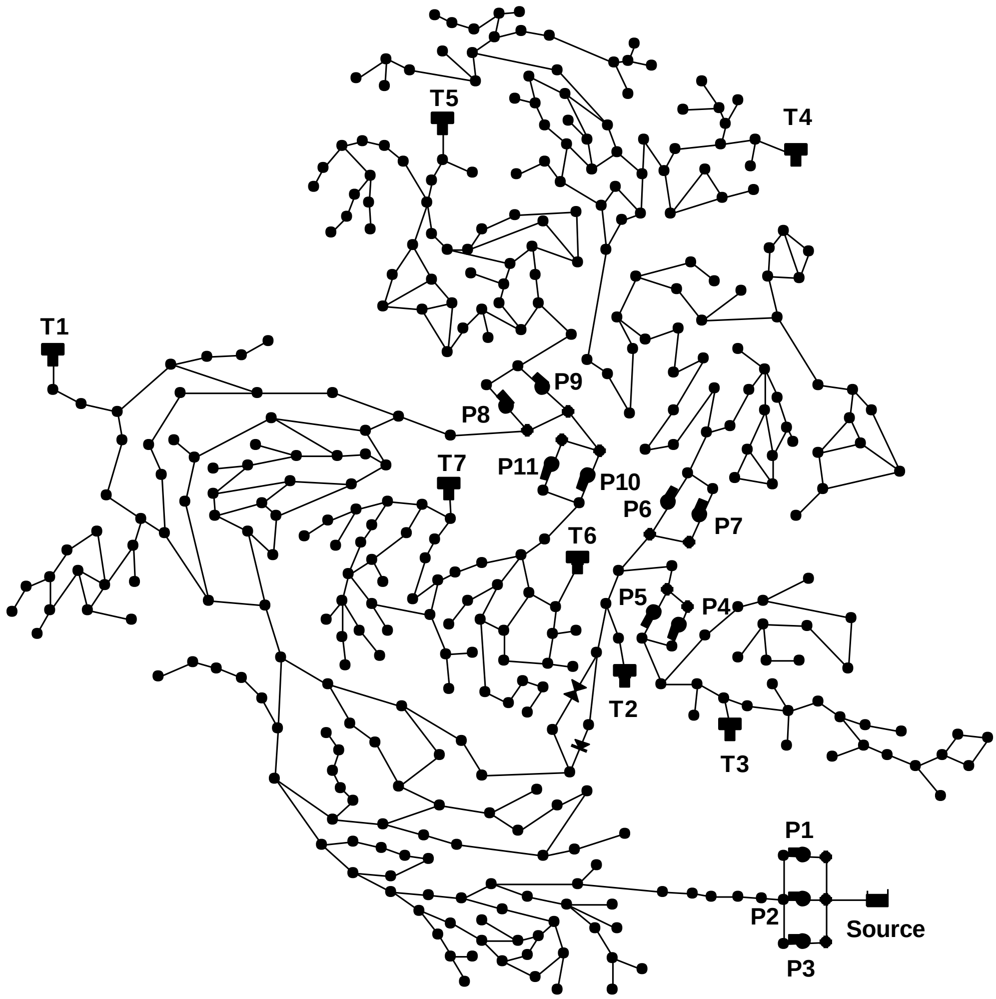


Figure 15. C-Town Network (adapted from Price and Ostfeld (2016)).

C-town network in Case A has exactly the same characteristics and initial conditions of the C-town network used in Price and Ostfeld (2016). It consists of 1 water source, 11 pumps, 7 tanks, 388 junctions, and 1 valve that is always opened. All pumps have fixed speed and assumed fixed efficiency of 70%. All pumps have multi-point characteristic curves as shown in Figure 16.

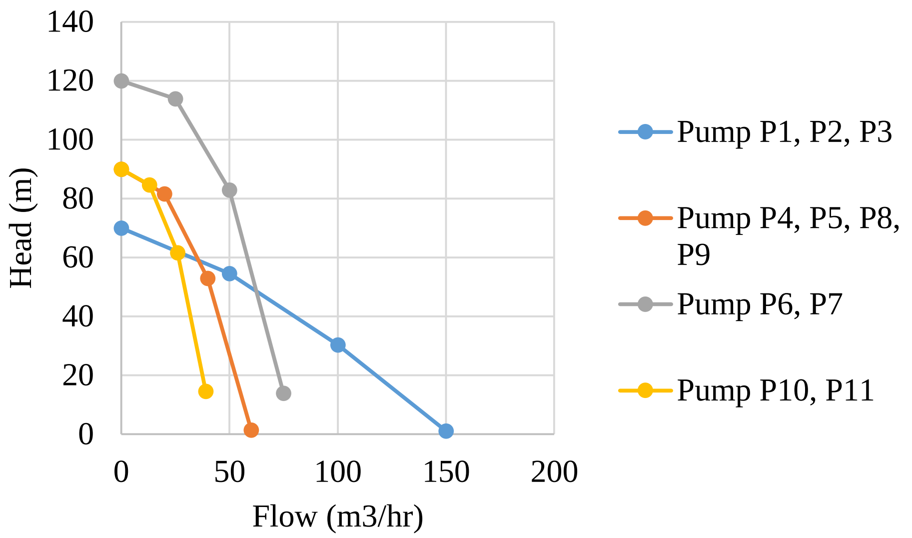


Figure 16. Case III pumps' characteristic curves

The details for all tanks in Case III is mentioned in Table 9.

Table 9. Tanks in Case III

| Tank | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| Elevation (m) | 71.5 | 65 | 112.9 | 132.5 | 105.8 | 101.5 | 102 |
| Diameter (m) | 31.3 | 20.78 | 13.73 | 11.64 | 11.89 | 8.33 | 7.14 |

The chlorine concentration upstream all pumps and inside tanks T2 and T6 is fixed at 0.50 mg/l. The initial chlorine value in all other tanks is 0 mg/l. Water mixing inside all tanks is assumed instantaneous and complete. First order bulk decay rate is -0.55 mg/l/day and first order wall decay rate is 0 m/day. As mentioned in Price and Ostfeld (2016), these water quality settings are made because the purpose is not to solve low chlorine problem in areas already suffering from low chlorine. The purpose is to prove that chlorine in WDSs can be improved through pump scheduling.

The pump scheduling (i.e. optimisation) time horizon is 7 days which is divided into 168 equal time steps of 1 hour length. Time step length in the hydraulic simulation is also 1 hour, while the water quality simulation time step is 5 minutes. The structure of the electricity tariff is shown in Figure 17.

The minimum chlorine concentration of 0.28 mg/l in all demand nodes is achieved by reducing the maximum water level of tanks T1 by 65%, T2 by 30%, T3 by 85%, and T4 by 15%. These percentages were found by Price and Ostfeld (2016) and fixed before running the iELGP method. The weight factor $w$ in Eq. (1) is set to 0 since improving water quality by minimising tanks inlet/outlet flow rate is not used.

In Case B, C-town network has exactly the same characteristics of C-town network in Case A except that tanks' maximum water levels are not reduced. The original maximum water levels in tanks WDSA (2014) are used. The minimum chlorine of 0.28 mg/l in all demand nodes is achieved by minimising tanks inlet/outlet flow rate. After careful water quality analysis of C-town network, it is found that demand nodes which are supplied from tank T3 are always suffering from low chlorine. The reason is that these demand nodes have low water demand compared to the size of pipes which are connected to. The low demand causes increase in travelling time (i.e. water age) and decrease in chlorine concentration. The analysis shows that by minimising tank T3 inlet/outlet flow, the chlorine in these demand nodes will be above than 0.28 mg/l. Minimising tank T3 inlet/outlet flow requires less running time of pumps P4 and P5 during each time step. This increases flow of other pumps (P6, P7, P8, P9, P10, and P11) and allow these pumps to supply more fresh water to their demand nodes and less water to their downstream tanks. Thus, by minimising tank T3 inlet/outlet flow, chlorine in all other demand nodes in the network is surprisingly improved to more than 0.28 mg/l.

In Case C, C-town network has exactly the same characteristics of C-town in Case B except that pumps P1, P2, and P3 have variable speeds. The fixed speed of these pumps in C-town networks analysed in Cases A and B is considered as maximum speed of these pumps in this Case C. The minimum water chlorine of 0.28 mg/l in all demand nodes is achieved by minimising tank T3 inlet/outlet flow rate.

The initial water levels in all tanks in all three cases are set equal to 50% of their maximum water levels. Minimum water level in all tanks is 0 m. Final water levels in all tanks are required to be at least equal to their initial water levels. Pump switches are not constrained because reducing number of pump switches increases water age and reduces chlorine in the network (Price and Ostfeld 2016).

The differences between the three types of C-town network are summarised in Table *10*.

Table 10. Comparison between the three cases of C-town network.

| **Case study III** | **Case A** | **Case B** | **Case C** |
|---|---|---|---|
| **Reaching the 0.28 mg/l minimum residual chlorine** | By reducing maximum water level of tank T1 by 65%, T2 by 30%, T3 by 85%, T4 by 15%. These percentages were found by Price and Ostfeld (2016) and fixed before iELGP optimisation. | By minimising inlet/outlet flow of tank T3 only (during the optimisation). | |
| **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 | | |
| **Pumps' speed** | Fixed | | Fixed except P1, P2, P3 |

## 4.4.3 Results

Using iELGP pump scheduling method, the operation of the C-town water network in Cases A, B, and C is optimised. Results obtained this way are compared with results obtained using the Graph theory methodology (Price and Ostfeld 2016) and summarised in Table 11.

Table 11. Comparison between the optimisation results for three C-town network cases (better performance values bolded and underlined)

| Case study III | | Case A | | Case B | Case C |
|---|---|---|---|---|---|
| Optimisation Method | | Graph theory (Price and Ostfeld 2016) | iELGP | iELGP | iELGP |
| Computer: Processor Model<br>Speed (GHz)<br>RAM (GB) | | Intel® Core™ i7-3770<br>3.40<br>8.0 | Intel® Core™ i7-3612<br>2.1<br>8.0 | | |
| 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 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 |

As it can be seen from Table 11, for Case A, the optimal pump schedule identified by iELGP method has lower energy cost of 381.10 $/day than the corresponding schedule identified by Price and Ostfeld (2016) which has energy cost of 395.40 $/day. However, the solution obtained from iELGP has higher number of pump switches than the solution identified by Price and Ostfeld (2016). This is because iELGP allows FSPs to run for fractions of time steps which gives more freedom for pumps operation in favour of more optimum energy cost. The computation time for iELGP (12.3 minutes) is lower than that for Graph theory (17.2 minutes) although Graph theory runs on a faster computer.

Figure 17 shows the optimal water levels in tanks obtained from iELGP for Case A of C-town network.

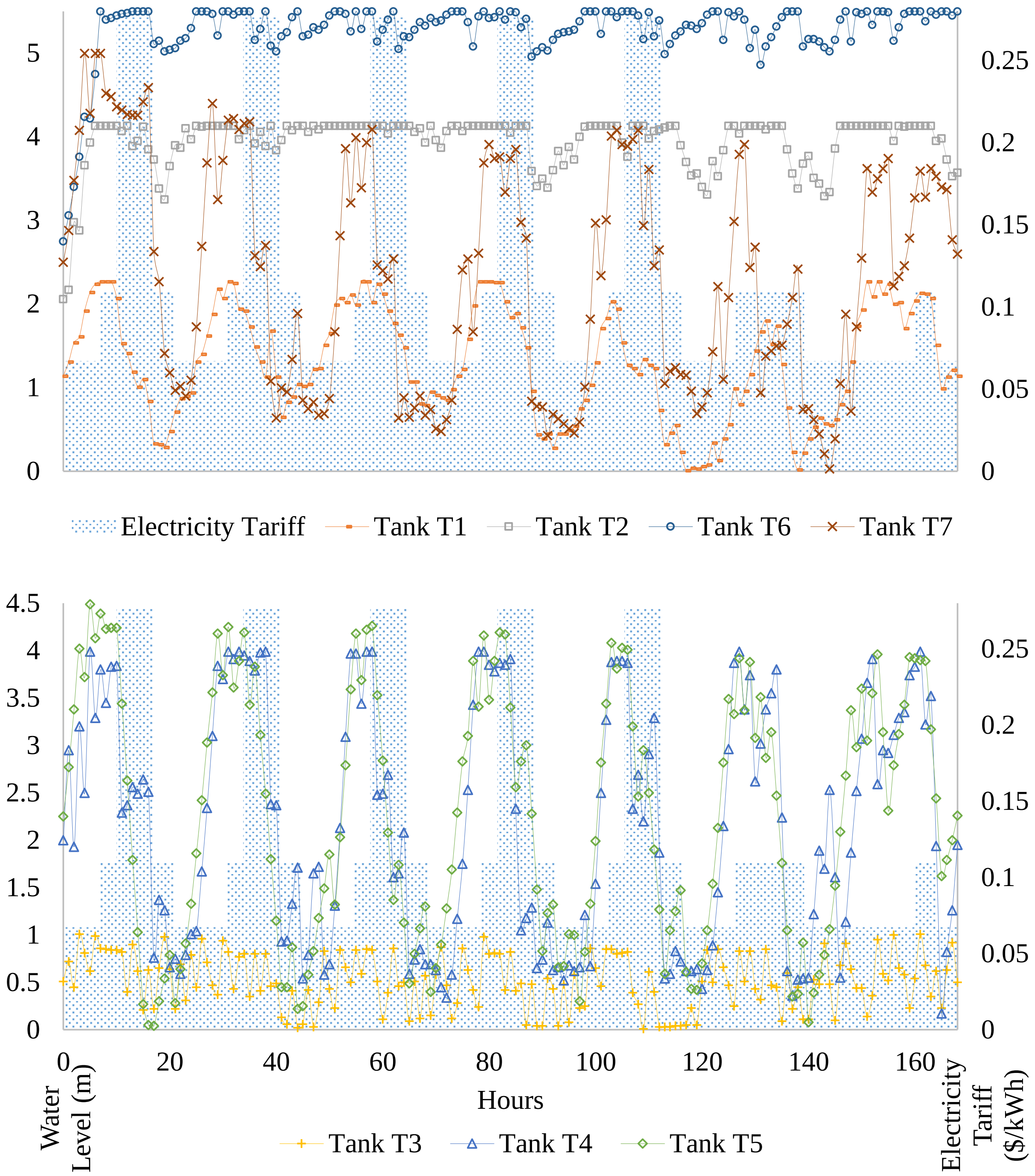


Figure 17. Optimum Tanks' water levels for C-town Case A obtained using iELGP

As it can be seen from Figure 17, water levels in tanks are increasing during the low electricity tariff and decreasing during the high electricity tariff. This is because, as expected, pumps are mostly running during the low electricity tariff and not running during the high electricity tariff. It can be seen also from Figure 17 that tanks final water levels are equal to or greater than tanks initial water levels, meaning that tanks are balancing well. Note also that tanks T2 and T6 have high water levels all the time. This is because these tanks have lower elevation than respective parallel tanks T1 and T7 as shown in Table 9. The high water levels in tanks T2 and T6 causes increase in their water age, and to avoid this chlorine is set to 0.5 mg/l inside these tanks as mentioned in the case study description (Section 4.4.2).

Table 11 shows also that pump schedule obtained from iELGP in Cases B and C have lower weighted average chlorine than that for Case A. This is because in Cases B and C, the minimum required chlorine of 0.28 mg/l in all demand nodes is achieved by minimising inlet/outlet flow rate for tank T3 only. However, in Case A the minimum required chlorine is achieved by minimising maximum water levels in tanks T1, T2, T3, and T4. Note that in Case B minimising tank T3 inlet/outlet flow rate is done automatically during the optimisation. However, in Case A tanks maximum water levels are set before optimisation through heuristic process that depends on trials and takes time (Price and Ostfeld 2016).

As shown in Table 11, changing pumps P1, P2, and P3 from FSPs in Case B to VSPs in Case C reduces the energy cost from $394.60 /day to $385.04 /day. Additionally, the total number of pump switches for pumps P1, P2, and P3 reduces from 34 to 6 hence reducing the related maintenance cost. The reduction of energy cost and number of pump switches in Case C is because P1, P2, and P3 run at lower speeds (i.e. lower energy cost) for longer periods of time. This is illustrated in Figure 18 which shows tank T1 optimum water level and optimum operation for pumps P1, P2, and P3 in Cases B and C. The figure shows that FSPs P1, P2, and P3 in Case B run with maximum speed during low and moderate electricity tariff and did not run during the high electricity tariff (except during time steps 12 and 14). However, in Case C, VSPs P1, P2, and P3 run most of the time but at the lowest relative speed of 0.70 (except for few time steps where relative speed is 0.80). Note also that the parallel identical VSPs P1, P2, and P3 in Case C run at equal speed, as constrained by Eq. (9) in Chapter 3, to equally share the load and reduce the total energy cost.

In addition to the above, note that the different operational scenario of pumps P1, P2, and P3 in Cases B and C makes water level in tank T1 (which is supplied by these pumps) different. As shown in Figure 18, in Case B water level in tank T1 increases (pumps are running) during low electricity tariff and decreases (pumps are not running) during high electricity tariff. However, Figure 18 shows that in Case C water level in tank T1 is increasing during the high electricity tariff. This is because during the high electricity tariff, the VSPs P1, P2, and P3 continue to run but the FSPs 4, 5, 6, 7, 8, 9, 10, and 11 which draw water from tank T1 do not run during the same tariff period.

Figure 18 shows also that in Case B the increase and decrease in tank T1 water level is relatively steep when compared to Case C. This is because in Case B pumps P1, P2, and P3 are FSPs that run either with maximum or zero speed, while in Case C these pumps are VSPs that run most of the time at the minimum speed of 0.70.

The operation behaviour of pumps P1, P2, and P3 in Case C causes an increase in number of water cycles (i.e. draining and refilling cycles) in tank T1compared to Case B. This allows water in tank T1 to reside for less time in Case C than in Case B. Additionally, the continuous run of water source pumps P1, P2, and P3 in Case C provides more fresh water to the whole network than in Case B. As consequence, the weighted average chlorine in the whole network in Case C (0.429 mg/l) is slightly higher than in Case B (0.419 mg/l). Thus, improved water quality is an advantage of using VSPs, in addition to the previously mentioned lower energy cost and number of pump switches.

Note that the iELGP computational time in Case C is almost twice the computation time in Case B. This is because in Case C, the decision variables for the VSPs P1, P2, and P3 are semi-continuous (pumps have either 0 relative speed or a value between 0.70 and 1.0). The time consuming Branch and Bound method is used to find the optimum value for these semi-continuous decision variables. However, in Case B, these pumps are FSPs and their decision variables, fractions of time steps during which pumps are running, are all continuous.

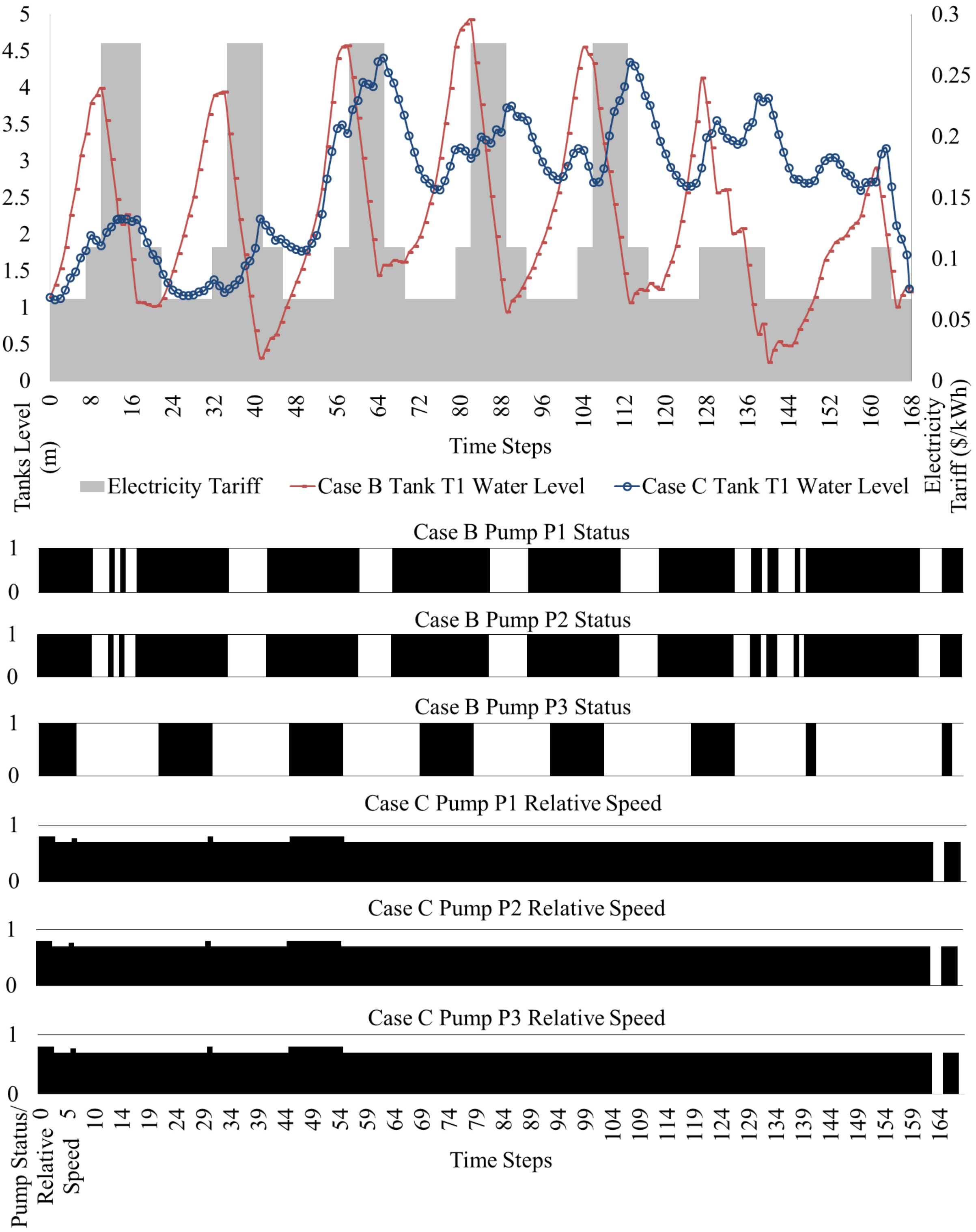


Figure 18. Comparison between Tank T1 water level in Case B and Case C. Also comparison between statuses of pumps P1, P2, P3 in Case B and Case C.

Figure 19 shows that chlorine concentration in tank T3 in Cases B and C, where the minimum chlorine of 0.28 mg/l in all demand nodes is achieved by minimising tank T3 inlet/outlet flow (chlorine values range between 0.37 and 0.45 mg/l). This is because tank T3 inlet/outlet flow rate is minimised to a level that does not worsen chlorine in this tank. In other words, tank T3 is allowed to exchange water but at minimum rate. More discussion about avoiding low chlorine in tanks can be found in discussion section 4.4.4.

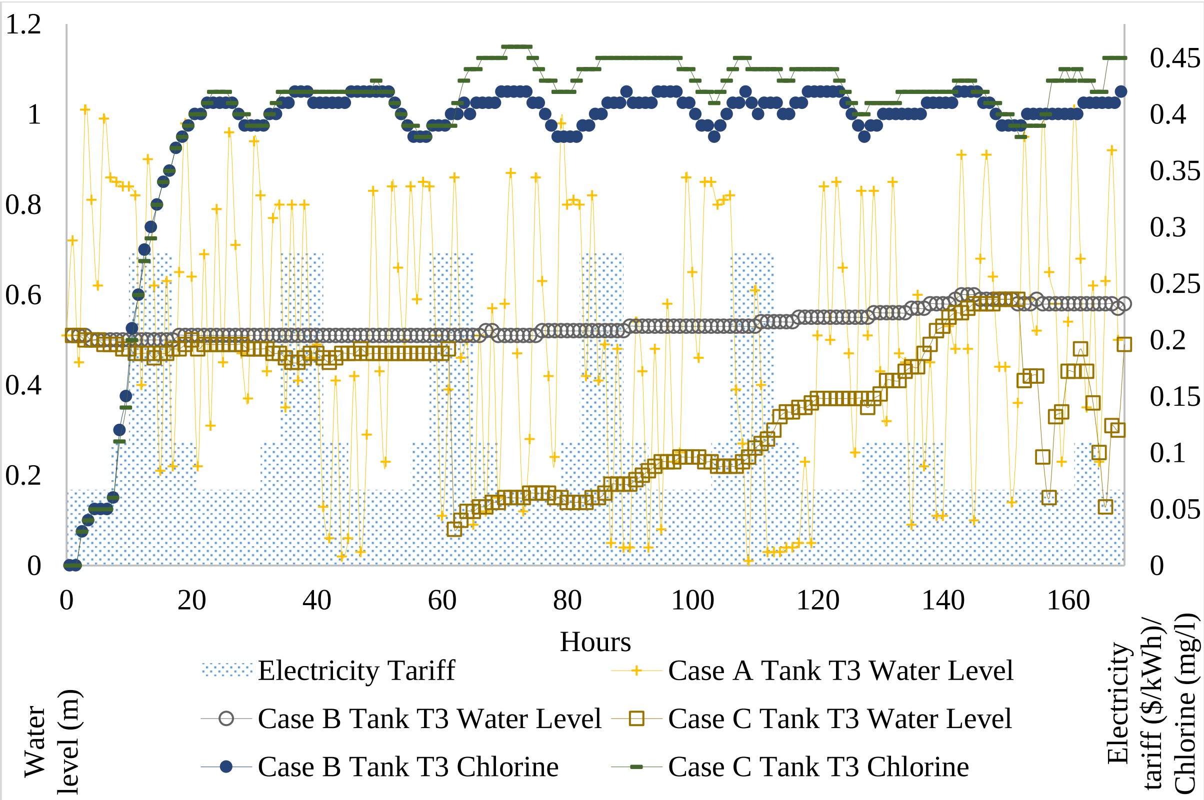


Figure 19. Optimum water level in tank T3 in C-Town Cases A, B, and C. Also, residual chlorine in tank T3 in C-Town Cases B and C. All obtained from iELGP.

In addition to the above, Figure 19 shows that water level in tank T3 in Case A of C-town has multiple hikes, which means that tank drains and refills frequently. This is because in Case A, tank T3 becomes very small (tank maximum water level is reduced by 85%). Opposite to this, in Cases B and C tank T3 water level is more gradually changing. This is because pump P4 which supplies tank T3 starts at the beginning of every time step to supply demand nodes and stops before the end of each time step to avoid storing excess amount of water in tank T3. Table 11 shows that pump P4 has 168 and 167 pump switches in Cases B, and C, respectively. This means that maintenance cost for pump P4 is expected to increase in favour of having good chlorine residuals in the whole network. Operator should alter the operation between pump P4 and pump P5 (which also supplies tank T3 but has 0 switches in Cases B and C) to reduce the number of pump switches for pump P4.

In Case C, pumps P1, P2, P3 (upstream of pump P4) are running continuously as shown in Figure 18. Thus, P4 has more flow in Case C than in Case B. Due to that, in Case C, P4 stopped at 60 hours and worked for small fractions of time steps at the end of the optimization time horizon which causes sudden drop in tank T3 water level in Figure 19. If pump P4 didn't stop at these times, then tank T3 final water level would be much higher than its initial water level and energy cost would be high, i.e. not optimal. This implies that iELGP works well with the aim to minimise both energy cost and water volume change in tanks.

Table 11 shows also that energy costs obtained using iELGP in Cases B and C are higher than the corresponding cost obtained using iELGP in Case A. This is because in Cases B and C, pump P4 which supplies tank T3, runs based on water demand regardless of electricity tariff. Thus, no saving is made in energy cost of pump P4.

In all Cases A, B, C of Case III, sometimes pressure drops below 20 m in 2 nodes which are J201 and J494.

Node J201 is supplied by gravity from tank T1 or pumps P1, P2, P3. Pumps P8, P9, P10, P11 are located downstream of node J201. The pressure in node J201 drops below 20 m sometimes when water level in tank T1 is low and pumps P8 and P11 are running. Figure 20 shows time series of node J201 pressure, tank T1 water level, pump 8 status, pump 10 status in Case A.

Figure 20 shows that pressure in node J201 is below 20 m when water level in Tank T1 is low and pumps P8 and P10 are both running.

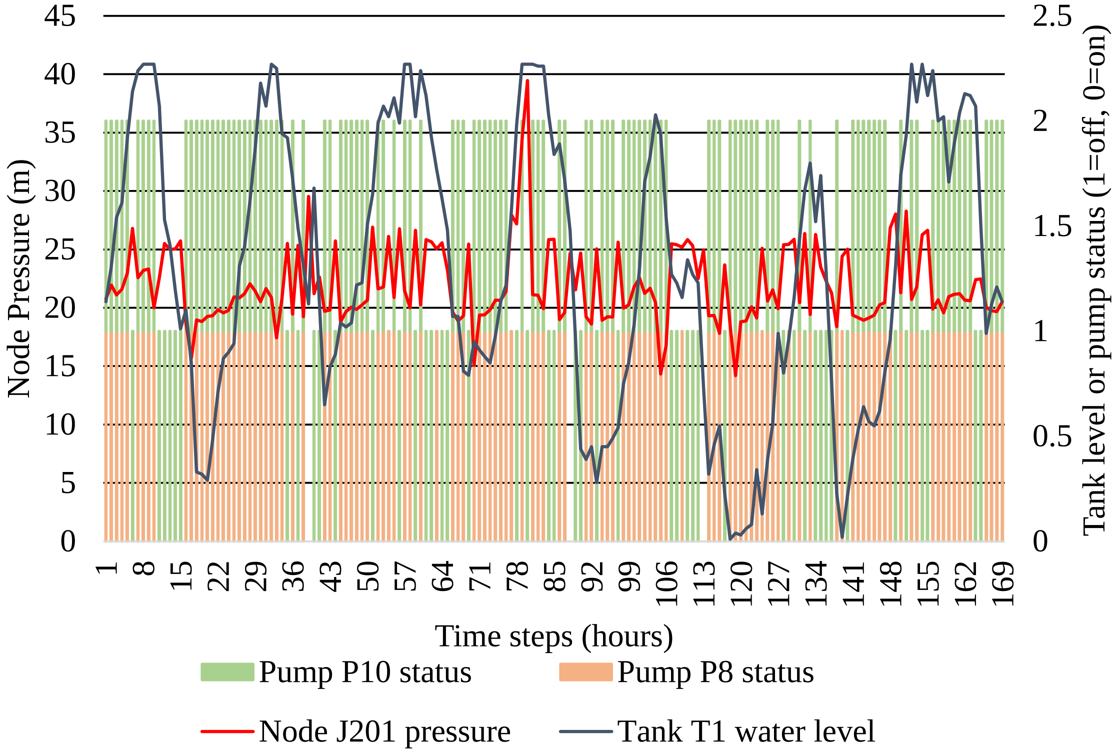


Figure 20. Pressure deficiency in node J201 in Case A of Case III

It is difficult to heursitically maintain pressure in node J201 above 20 m, because it is related to the operation of pumps P1, P2, P3, P8, P9, P10, P11. A pressure constraint should be imposed in the optimization model to ensure that pressure at node J201 is always above 20 m.

Node J494 is supplied by gravity from tank T4 or pumps P6 and P7. Pressure in node J494 drops below 20 m whenever pumps P6 and P7 are stopped, regardless of the water level in tank T4. Running pump P6 or P7 all the time is not possible because it will cause overflow in tank T4. The deficiency in J494 is design problem and it is not related to the optimum pump schedule.

Pressure in all other demand nodes (332 nodes) is always above 20 m.

## 4.4.4 Discussion

Based on the results shown in the previous section, the following observations / discussions are made here:

- A comparison of pump scheduling results obtained using the iELGP and Graph theory (Price and Ostfeld 2016) methods for Case A of this case study indicates that there is a trade-off between energy cost and number of pump switches. Decreasing energy cost might cause an increase in the number of pump switches.
- Minimising tank T3 inlet/outlet flow rate in Case B and Case C did not cause decrease in chlorine inside tank T3, as shown in Figure 19. However, if the method of minimising tank's inlet/outlet flow rate is applied on different case study, then chlorine might decrease inside the tank due to increase of water age. Decision maker in this case should reduce the weighting factor $w$ (see Eq. (1) in Chapter 3). This will reduce the weight of minimising tank's inlet/outlet flow rate in the objective function (second term in Eq. (1)) and the iELGP optimisation method will focus more on minimising the energy cost (first term in Eq. (1)). Thus, the tank will have more freedom to gain and drain water which will eventually decrease water age and increase chlorine inside the tank. To elaborate further on this point, the two objectives, minimising energy cost and tank inlet/outlet flow, contradict each other. Minimising energy cost by running pumps during the low electricity tariff and stopping pumps during the high electricity tariff increases the tank's inlet/outlet flow rate which will eventually increase water age in the network. In contrast, running pumps based on demand only regardless of electrical tariff increases the energy cost and minimises the tank inlet/outlet flow rate which will eventually decrease water age in the network.
- Once the value of the weighting factor $w$ is determined (as explained in Chapter 3 and as discussed in the previous bullet), the minimum required chlorine in the network should be fulfilled every time the iELGP optimisation method is run. However, if there is a major change in the demand patterns or the network configuration, then the value of the weighting factor $w$ should be changed to reflect these changes.
- Several research papers concluded that reducing VSPs speed (and thus VSPs flow rate) decreases the chlorine decay (Ramos, et al. 2010; Mohammed and Khudiar 2012; Jamwal and Kumar 2016). This is because lower water flow rate reduces pipe wall reaction and biofilm

removal. However, this effect of VSPs in chlorine decay does not appear in Case C of this case study, because the water quality simulator (*EPANET 2.0.12*) does not account for mass flux between the water flow rate and pipe wall.

- Before deciding to make new investment and replace FSP with VSP, we should not only look at the savings in energy cost, maintenance cost, and improvements in water quality. We should also check capital cost, interest rate, and payback period to ensure that the investment is worthy.
- Comparing the computational time that iELGP takes in Case studies I, II, and III, it can be concluded that the computational time increases with the following:
    - An increase in the number of time steps (iELGP takes 4 seconds to optimise Case study II that has 3 time steps, while it takes 12.3 minutes to optimise Case A of Case study III that has 168 time steps);
    - An increase in the network size (iELGP takes 2.15 minutes to optimise Case study I that has small size network while it takes 12.3 minutes to optimise Case A of Case study III that has medium size network);
    - An increase in the number of VSPs (iELGP takes 11.90 minutes to optimise Case B of Case study III that has no VSPs while it takes 22.70 minutes to optimise Case C of Case study III that has 3 VSPs).

  This conclusion seems to be common knowledge. However, this conclusion is necessary to emphasize on factors that affect the computational time. Understanding these factors will help decision maker to improve the performance of iELGP pump scheduling method.
- The ability of the iELGP method to find optimum pump schedules in all three case studies represents a good basis for application of this method to other real water networks with different characteristics.

## 4.5 Summary

In this chapter, the pump scheduling method iELGP presented in Chapter 3 is tested, validated and demonstrated on three case studies. The objective in the first and second case studies is to minimise energy cost only, whereas in the third case study, energy cost and water age are minimized simultaneously. The corresponding WDSs analysed in the case studies have different topographies, demand patterns, electricity tariff structures, optimization time horizon, numbers of pumps and tanks.

Results obtained using the iELGP method are compared with the results obtained using other literature pump scheduling methods that were applied to the same case studies. The results obtained prove that the iELGP method is a powerful pump scheduling method in terms of optimality of the solution and computational efficiency.

The objectives of the optimisation that are set in section 1.3 in Chapter 1 are successfully attained in this chapter. The following Table 12 recalls these objectives and how they are addressed in this chapter.

Table 12. Optimisation objectives and case studies

| **Optimisation objectives: to develop a pump scheduling method that** | **How each objective is demonstrated in the case studies** |
|---|---|
| 1- Minimises energy cost | In all three case studies, iELGP gives lower energy cost pump schedules compared to pump schedules obtained from other methods that were applied on the same case studies. |
| 2- Improves water quality | Chlorine (a surrogate indicator of water quality) is improved by reducing tanks' maximum water levels or minimising tanks' inlet/outlet flow rates, as shown in Case study III. |

| | |
|---|---|
| 3- Reduces maintenance cost | Number of pump switches (a surrogate indicator of maintenance cost) are reduced implicitly by increasing the length of time steps as in Case study II. |
| 4- Optimises the operation of variable speed pumps. | The method identifies optimum speed for VSPs as shown in Case C of Case study III. |
| 5- Can be applied on any type of WDS. | The pump scheduling method is tested on three different case studies that have different topography, number of pumps, number of tanks, demand patterns, optimisation time horizon length, and electricity tariff. Results show that iELGP is a general pump scheduling method that is not tailored for specific type of WDS.<br><br>The application of iELGP on WDSs where minimum pressure at demand nodes and optimum valves operation are required has not been implemented. This is left for future developments as mentioned in Chapter 5. |
| 6- In a computationally efficient manner. | iELGP is able to identify optimum pump schedule within short computational time using normal computer, as shown in all three case studies. Thus, the method is suitable for real-time application. |

# Chapter 5: Conclusions

## 5.1 Summary of the work done

This thesis starts with Chapter 1 which introduces the two problems of energy cost and water quality that become big concern for the world in general and for water utilities in particular. Then it introduces pump scheduling as a solution to minimise energy cost and improve water quality in water distribution systems. However, solving pump scheduling problem is not straight forward due to reasons that are listed in Chapter 1. Upon that, research questions and objectives are set-up.

Chapter 2 reviews more than 250 published papers about pump scheduling. This large number of published papers indicates how important the pump scheduling is. In order to easily compare this big number of papers, the general framework of any pump scheduling method is divided into three parts: hydraulic model, optimisation model, and optimisation method. The contribution of the previous pump scheduling methods in these three parts is presented in details. The drawbacks in the previous pump scheduling methods are extracted.

Chapter 3 describes the new pump scheduling method named as iterative Extended Lexicographic Goal Programming (iELGP). The assumptions that are used in the methodology are listed first. Then, the equations that formulates the new pump scheduling method are presented. After that, the solution steps are listed sequentially and shown in process flow chart.

Chapter 4 contains three case studies that are used to test the effectiveness of iELGP. The details of each case study are described. Then, results obtained from iELGP for each case study are presented and discussed. Results obtained from iELGP are compared with results obtained from previous pump scheduling methods that were applied on the same case studies.

This Chapter 5 summarises and concludes the work done in this thesis.

## 5.2 Conclusions

The following key conclusions are drawn based on the results obtained from application of new pump scheduling methodology iELGP to case studies analysed in this thesis:

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 results obtained using iELGP were compared to the results obtained using several literature methods for pump scheduling. In the case when water quality is not optimised, when compared to the results obtained by using the iLP method (Price and Ostfeld 2013), the iELGP methods developed in this thesis identified a better, lower cost pumping solution in a slightly less computational manner and with marginally larger number of pump switches (which were not constrained in iELGP). When compared to the HGA method (van Zyl, et al. 2004) and the ACO method (López-Ibáñez, et al. 2008) on the Richmond case study, the iELGP method identified better, lower energy cost pump schedules and in a much more computationally efficient manner with lower number of (this time constrained) pump switches. An additional advantage of the iELGP methods when compared to HGA and ACO methods is that it does not have any search parameters that need to be fine-tuned before running the optimization. As a consequence, iELGP method needs to be run once only whilst optimization methods like ACO and HGA need to be run several times to ensure obtaining optimal schedules.
3. In the case when water quality was optimised for together with cost of energy, 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 but at the cost of increased number of pump switches (even though neither of the two methods constrained this). Two different approaches were used to improve water quality (i.e. increase residual chlorine) whilst scheduling pumps: by reducing tanks' maximum water levels and by minimizing tanks' in/out flows. As demonstrated on the C-Town case study, 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.

## 5.3 Summary of Thesis Contributions

Pump scheduling in WDSs is not a new subject. As demonstrated in the literature review in Chapter 2, there are more than 250 papers published on the topic of pump scheduling in the last five decades. Despite the fact that some of these methods were implemented successfully by water utilities (Fallside and Perry 1975; Alla and Jarrige 1988; Ulanicki and Orr 1991; Brdys and Ulanicki 1994), a number of limitations remain in literature pump scheduling methods.

The principal thesis contributions are as follows:

1. Development of novel, optimisation based problem formulation for pump scheduling problem. The formulation enables simultaneously optimising the cost of energy used for pumping whilst maintaining water quality in a water distribution system.
2. Development of a new, optimisation based iELGP method that is capable of solving effectively and efficiently the above pump scheduling problem.
3. Testing, validation and demonstration of advantages and limitations of iELGP pump scheduling method on three different case studies. The objective in the first and second case studies is to minimise energy cost only, whereas in the third case study, energy cost and water age are minimized simultaneously.

More specifically, the new iELGP pump scheduling method overcomes the aforementioned limitations in existing literature approaches as follows:

1- Several existing pump scheduling methods generate suboptimal solutions due to relevant simplifications in the hydraulic or the mathematical optimisation models (see Chapter 2). Although the iELGP method developed in this thesis is also based on certain assumptions (Chapter 3), these are made in the way that improves the computational efficiency of the pump scheduling method without loss of accuracy. This is clearly proven in all case studies analysed in Chapter 4, where pump schedules and other results obtained using the iELGP are more optimal than the corresponding results obtained using several literature methods.

2- Existing single objective pump scheduling methods focus on minimising the energy cost and, as a consequence, pump schedules generated this way may worsen water quality in a distribution system. The iELGP pump scheduling method developed in this thesis overcomes this issue by formulating and solving a multi-objective optimisation problem that simultaneously minimises the cost of energy whilst maintaining the water quality.

   In Chapter 4 of this thesis, the objective in Cases I and II was to minimise energy cost only. Results show that water age is high for few hours in Case I and in farthest away nodes in Case II. In Case III, the objectives were to minimise energy cost and water age simultaneously. Thus, in Case III there was no issue with water age in demand nodes.

3- Water utilities are using increasingly VSPs because they provide better pressure control in the network. However, most existing pump scheduling methods are not capable of optimising the operation of VSPs. The iELGP pump scheduling method developed in this thesis can optimise the operation of a general WDS containing a mixture of fixed and variable speed pumps.

4- Several existing pump scheduling method are tailored to specific type of WDS. The iELGP pump scheduling method developed in this thesis is tested and validated on three different case studies that have different topography, demand patterns, number of pumps, number of tanks, and electricity tariffs. The results obtained on these case studies prove that iELGP is able to produce optimal, realistic pump schedules in all cases analysed.

5- Computational time is a significant burden that obstructs many existing pump scheduling methods from being implemented for real-time control. Additionally, several existing pump scheduling methods have search parameters that need to be tuned or the method should be run several times to ensure obtaining optimum solution. The iELGP pump scheduling method developed in this thesis can generate optimal pump schedules for large real life water networks in a computationally efficient manner. Additionally, unlike stochastic search methods, the iELGP is a deterministic method that obtains the optimal pump schedule using a single optimisation run (and this solution is always the same, even if method is ran more than once).

## 5.4 Recommendations for Future Work

Like any other research work, the work completed in this thesis is not without limitations. The IELGP method presented in the thesis could be further improved as follows:

1- Goal programming methodology that is used as a basis for developing the iELGP method is often criticised for producing Pareto inefficient solutions. However, several effective techniques exist for detecting and restoring Pareto efficiency (Cohon 1978; Jones and Tamiz 2010). These techniques should be used in future work to ensure that the weighting factor $w$ in Eq. (1), target value $ECT$ in Eq. (2) and $VCT_a$ in Eq. (13) are properly set.

2- The iELGP pump scheduling method does not account for maximum power demand charge. Although the charges based on energy use are more common than the charge based on maximum power demand, it would be better to generalise iELGP and enable it to account for maximum power demand charge as well. This will extend the applications of iELGP and increase its popularity.

3- Water demand in pump scheduling is considered as disturbance variable because it keeps changing and it is difficult to predict accuratly. To cope with this, the iELGP pump scheduling method need to be coupled with a water demand forecasting method before used for real-time pump scheduling.

4- Further testing on even larger and more complex real network that rquires operation of valves and minimum pressure at demand nodes. This is to better understand the limitations of the iELGP method and improve its capabilities.

5- Optimum pump schedule obtained using iELGP method might cause pressure deficiency in some demand nodes. To avoid this, pressure constraint should be imposed in the optimisation model.

# Appendix: Summary of existing pump scheduling approaches

| ID. Authors (Year) SO/MO* | Optimisation model (Objective Function+, constraints**, decision variables++) | Water quality Network analysis Optimisation method | Notes |
|---|---|---|---|
| 1. Carrijo et al. (2004) MO | Objective function: (1) minimise energy cost and maximum demand charge. (2) Meet pressure at demand nodes, minimum water level in tanks, and water demand.<br>Constraints: no constraints<br>Decision variables: pump status (binary) and valve status (binary). | Water quality: N/A<br>Network analysis: EPANET (EPS)<br>Optimisation method: SPEA | - Data mining process on big classified operational data is used to reduce the number of possible solutions. The data mining program is named SEE5.<br>- Test network: macro system (skeleton) of the city of Goiânia, Brazil.<br>- Solutions that have few pump switches are classified as excellent. |
| 2. Sousa et al. (2006) SO | Objective function: minimise energy cost, maximum demand charge, and number of | Water quality: N/A<br>Network analysis: explicit mathematical | - The method copes with a complex electricity tariff structure.<br>- Test network: hypothetical netowork of three sources, three pumps, and three tanks.<br>- Replacing fixed speed pumps with variable speed pumps |

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| | pump switches.<br>Constraints: min/max pressure, min/max flow in pipes, minimum final water levels in tanks.<br>Decision variables: pumps' statuses (binary), pump speed (discrete). | equations.<br>Optimisation method: Simulated Annealing | could reduce energy cost and pressure. |
| **3. Abiodun and Ismail (2013)**<br>**SO** | Objective function: minimise energy cost and maintenance cost.<br>Constraints: No special constraints.<br>Decision variables: pumps' statuses (binary). | Water quality: N/A<br>Network analysis: hydraulic requirements are assumed to be satisfied.<br>Optimisation method: Genetic algorithms | - Adaptive weights multipliers are used for adding energy cost to maintenance cost in single objective function.<br>- A repair strategy is used if offspring chromosomes do not satisfy tank min/max water level constraint.<br>- Test network: hypothetical network of one source, five pumps, one tank, and one demand node.<br>- The performance of the method is compared with simple fix weigh genetic algorithm and random weight genetic algorithm. |
| **4. Skworcow et al. (2014)** | Objective function: minimise energy cost and water treatment cost. | Water quality: N/A<br>Network analysis: EPANET.<br>Optimisation | - Model reduction algorithm was used to reduce size of big networks.<br>- Leakage was added to mass balance equation at connection nodes. |

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| | Constraints: min/max pressure at critical nodes, final water levels in tanks are at least equal to their initial levels, min/max values for decision variables. Decision variables: pumps' statues, pumps' speed, pressure reducing valves settings, water treatment flow. | method: generalised reduced gradient algorithm | - A heuristic automatic method and another interactive method are used to transform continuous pump schedules to discrete pump schedules. - Test network: large scale water distribution network being part of major UK water company. It consists of 4 sources, 10 tanks, 12923 pipes, 12363 nodes, 13 pumps, 315 valves. - Sensitivity analysis is performed by using different leakages, initial tanks' levels, and demands. |
| **5. Abkenar et al. (2015)** | Objective function: minimise energy cost and penalty for violating min/max pressure constraint. Decision variable: pump speed (discrete). | Water quality: N/A Network analysis: EPS Optimisation method: Genetic Algorithms | - Pump scheduling problem are described in two different ways, using continuous and discrete decision variables. - The two different representations have different procedures for mutation and crossover. - Pollutant Emission and Pump Station Optimization (PEPSO) software is used. - Authors concluded that using discrete methods requires more computational time but avoid producing equal solutions compared to continuous methods. |

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| | | | - Test network: Monroe, MI, USA. |
| **6. Costa et al. (2015) SO** | Objective: minimise energy cost.<br>Constraint: maximum number of pump switches, minimum/maximum pressure at demand nodes.<br>Decision variables: pump statuses (binary) | Water quality: N/A<br>Network analysis: EPANET (EPS)<br>Optimisation method: Branch and Bound | - Test Network: a modified Any town that has one source, three pumps, and three tanks.<br>- The results show trade-off between optimality of the solution and computational efficiency.<br>- Authors stated that the more constraints the more efficient branch and bound method becomes. |
| **7. De Paola et al. (2016) MO** | Objectives: (1) minimise energy cost and penalties (2) minimise number of pump switches.<br>Constraints: maximum number of pump switches, pump maximum flow, final water levels in tanks are at least equal to their | Water quality: N/A<br>Network analysis: EPANET (EPS)<br>Optimisation method: harmony-search multi-objective | - Termination criteria: maximum number of function evaluations is reached.<br>- Test network: Any-town network with four pumps and one tank.<br>- Authors compared their results with results obtained from genetic algorithm optimisation method on the same test network. The comparison shows that harmony search is competitive to genetic algorithm. |

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| | initial levels. Decision variables: pumps' statuses. | | |
| **8. Menke et al. (2016c) SO** | Objective: minimise energy cost. Constraint: maximum number of pump switches. Decision variables: pumps' statuses (binary) | Water quality: N/A Network analysis: explicit mathematical equations Optimisation method: Branch and Bound | - Reduction of symmetry in identical pumps reduces the computational time. - Loops in water networks and number of time steps can increase the computational time. - Network size has less influence on computational time. - Linear and quadratic approximations are investigated. Results show that linear approximation outperform quadratic approximation, taking into consideration the demand uncertainties and the required accuracy in water networks. - Optimum solutions are simulated using a hydraulic simulator to check accuracy. - Test networks: B-town and three modified Van Zyl et al. (2004) artificial networks. |
| **9. Khatavkar and Mays (2017) SO** | Objective: minimise energy cost. Constraint: maximum number of pump switches | Water quality: N/A Network analysis: Explicit mathematical equations | - Uncertainty in demand is modelled using with chance constraint with mean and standard deviation values. - Increasing the uncertainty in demand might further reduce the operation cost. - The method can be further used for emergency cases. |

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| | Decision variables: pumps' statuses (integer), pumps' flow and pressure (continuous) | Optimisation method: simulated annealing. | - Test network: hypothetical network of 10 pumps. |
| **10. Bonvin et al. (2017) SO** | Objective function: minimise energy cost. Constraints: no special constraints. Decision variables: pumps' statuses (binary) and flow through pipes, pumps, or valves (continuns) | Water quality: N/A Network analysis: Explicit mathematical equations Optimisation Method: Mixed Integer Quadratically Constrained Programs | - The method is pure model-based approach that relies on convex relaxation and tractable mathematical program. - The method is sensitive to dynamic electricity pricing, thus it can be used for demand-response. - Test network: FRD network in France. It consists of 6 pumps, 16 tanks, 49 nodes, and 53 pipes. |
| **11. Makaremi et al. (2017) MO** | Objectives: minimise (1) energy cost and maximum demand charge (2) number of pump switches. Constraints: | Water quality: N/A Network analysis: EPANET (EPS) Optimisation method: Non-Dominated Sorting | - The optimisation method is made self-adaptive to satisfy constraints. - Population is sorted based on feasibility, non-domination, and crowding-distance. - Test networks: van Zyl et al. (2004) artificial network and Baghmalek water network which consists of 1 source, 1 tank, |

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| | min/maximum pressure at demand nodes, pump maximum flow, tanks' final volume is greater than initial (very small tolerance is considered)<br>Decision variables: pumps' statuses (binary). | Genetic Algorithm II | 6 pumps, 34 pipes, and 32 nodes.<br>- Optimisation method has to be run several times because it is a stochastic method. |
| **12. Luna et al. (2018) SO** | Objective(s): Minimise energy cost and penalty for violating min/max water level in tanks.<br>Constraints: no special constraints.<br>Decision variables: pump status. | Water quality: N/A<br>Network analysis: EPANET (EPS)<br>Optimisation method: Genetic Algorithm | - For a group of identical parallel pumps, the decision variable can be an integer that represents the number of running pump during each time step. This reduces the computation time.<br>- To improve optimality and convergence, knowledge based individuals are added to initial population.<br>- The effect of tanks water level constraint on energy cost is investigated.<br>- The optimisation module is coded in PYTHON.<br>- Test network: four pumping stations connected to four tanks in Algarve, Portugal. |
| **13. Torregrossa** | Objectives: minimize energy cost and penalty | Water Quality: N/A<br>Network Analysis: | - The method integrates two aspects of pumping systems, which are cavitation and overflow from water source. |

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| **and Capitanescu (2019)**<br>**SO** | for violating constraints.<br>Constraints: maximum flow from water source, maximum number of pump switches, and cavitation.<br>Decision variables: optimum water level in tank that activate pumps. | EPANET (EPS)<br>Optimisation Method: genetic algorithm, simulated annealing, and particle swarm optimization. | - Optimum water levels in tank that activate pumps are considered constant in one approach and dynamic in another approach.<br>- Authors claimed that particle swarm optimisation and simulated annealing algorithm are better than genetic algorithm for solving pump scheduling problem.<br>- Time step length is 5 minutes.<br>- Test network: hypothetical network with one source, one tank, and two pumps. |

Note: *SO: Single-objective, MO: Multi-objective. +Objective function is referred to as 'objective' in the column below due to space savings. **Constraints that represent conservation of mass of flow, conservation of energy, and conservation of mass of constituent (for water quality network analysis), tanks minimum and maximum water levels, tanks final level not less than initial level, are not listed. ++Control variables are listed, state variables resulting from network hydraulics are not necessarily listed. ?D: Design. ??OP: Operation.

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