Quantifying the Energy Consumption of the Water Use Cycle

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To Claudia,

Who encouraged me to run

Literally, on those sunny evenings in Uni Parks, and

Figuratively, by pushing me to chase my dreams.

You were taken too soon from us,

But you will leave a lasting impact.

I dedicate my work to you, with tears in my eyes.

I find it hard to write, but I know you would be laughing now.

It is different without you, but

I will make sure to think of you in the rivers, and in the ocean,

To show you how much I learnt from you,

I carry you with me, always,

With your cheeky smile,

Drawing mischief with your eyes.

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Abstract

The management and delivery of water and wastewater consume significant amounts of energy, mostly in the form of electricity. With increasing populations, climate change, water quality issues and increasing energy prices, it is more important than ever to understand energy consumption patterns. Energy usually represents the largest operational cost in water utilities around the world, yet there is limited work aiming to quantify the specific relationship between water and its associated energy, and understand its implications for future decision-making.

This thesis presents various methodological approaches to quantify and understand energy use in water infrastructure systems, as well as how to incorporate them in decision-making processes. The main hypotheses are as follows: firstly, a detailed understanding of the use of energy in water infrastructure systems can facilitate more efficient and sustainable water infrastructure systems and, secondly, that incorporating energy into planning for water and wastewater resources can help understand the impacts of decisions and establish trade-offs between actions.

To test these hypotheses, the thesis presents an analytical approach to various areas. Firstly, it identifies, maps and quantifies the energy consumption patterns within a water infrastructure system. This is then used to identify inefficiencies and areas of potential energy saving. Secondly, it incorporates detailed energy costs into short and long-term water resources management and planning. Thirdly, it evaluates trade-offs between energy costs and changing effluent quality regulations in wastewater resources. The Thames River basin, in the south-east of England, is used as a case study to illustrate the approach.

The results demonstrate that a systematic approach to the quantification of energy use in a water infrastructure system can identify areas of inefficiencies that can be used to make decisions with regards to infrastructure planning. For example, water systems have significant geo-spatial variations in energy consumption patterns that can be addressed specifically to reduce negative trade-offs. The results also show that incorporating detailed energy information into long-term water resources planning can

alter the choices made in water supply options, by providing more complete information. Furthermore, methodologically, they show how several methodological approaches can be used to support more complete decision-making in water utilities to reduce short and long-term costs.

In this particular case study, the results show that there are important differences in energy consumption by region, and significant differences in the seasonal and energy patterns of water infrastructure systems. For example, water treatment was shown to be the largest consumer of energy within the whole system, compared with pumping or wastewater treatment; but wastewater treatment energy consumption was shown to be the fastest growing over time due to changes in water quality regulatory frameworks. The results show that more stringent effluent standards could result in at least a doubling of electricity consumption and an increase of between 1.29 and 2.30 additional million tonnes of CO_2 a year from treating wastewater in large works in the UK. These are projected to continue to increase if the decarbonisation of the electricity grid does not occur fast enough. Finally, the thesis also shows that daily energy consumption can be reduced by up to 18% by optimally routing water through a water network. optimization of water networks, and that a change in discount rates could change the daily operating costs by 19%, that in turn leads to a resulting different set of optimal investment options in a water supply network.

Publications

The work presented in Chapters 3 to 6 has been submitted to the following peer-reviewed journals:

1. Cárdenes, I., Eyre, N., Hall., J. W., Colquhoun K. (2017). Submitted to *Water Resources Management* (Chapter 3).
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3. Cárdenes, I., Hall., J. W., Eyre, N., Jarvis, S. (2017). Submitted to *Water Research* (Chapter 5).
4. Cárdenes, I., Siddiqi, A., Mortazavi-Naeini M., Hall., J. W., Eyre, N. (2017). Submitted to *Environmental Science & Technology* (Chapter 6).

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1. Introduction

1.1 Background

Two of the greatest challenges we face are the provision of clean water and the provision of energy to an ever-expanding population in the face of climate change. In the context of the Sustainable Development Goals adopted by the international community, these issues take global priority: achieving clean water and appropriate sanitation for all will require large investments in infrastructure world-wide to provide adequate access, whilst investment in renewable energies will be key to avoid a global economy reliant on fossil fuels and the increase of greenhouse gas emissions (UN DESA 2015). According to the United Nations, approximately 8% of global energy supply is currently used to deliver and manage water (UN Water 2014; UN WWAP 2014). Large quantities of energy are needed to convey water through infrastructure systems, with the total energy consumed for these operations rising globally (Ofwat 2010c). With 1.6 billion people lacking access to the necessary infrastructure to deliver and manage water, the challenge is to better understand this relationship to meet the global need for clean water.

Traditionally, the fields of energy systems and water systems have been managed in isolation. Clear examples of the interaction of the water and energy sectors are apparent when considering the importance of desalination (an energy intensive process) to deal with water scarcity or the harnessing of hydropower to meet our expanding energy demands. Research that has described coupled water-energy challenges has focused mostly on the water use of the energy production sector (water for power generation) (e.g. Byers et al. 2014; Mielke et al. 2010; Vine 2012), not on energy for water provision, and not in a whole-system manner (Barry 2007). When there has been a focus on the water sector, it is usually technology specific, or on a specific component, but rarely with a 'whole system' approach (Cook, Hall, and Gregory 2012). Energy in the water and wastewater sector however, offers significant opportunities to save energy and save water, both crucial for human development.

Energy and water systems both face increasing stresses from climate change. In the water sector, concerns focus on the impacts of projected changes to water availability, i.e. climate adaptation. In the energy sector, the predominant concern is climate mitigation. In fact, the energy sector has been repeatedly assessed in relation to greenhouse gas emissions and carbon abatement costs of various energy supply options (IEA 2015). Both point to an increased emphasis on resource conservation with a stronger role for investment and behavioural change by final consumers, i.e. increased water and energy efficiency. Despite the commonalities however, there is little tradition of policy cross learning between the sectors globally. There is a significant degree of policy fragmentation that is seeing erroneous developments in the sectors, both in industrialized and industrializing nations (Hussey and Pittock 2012). In some regions around the world, ignoring underlying interdependencies has led to policies having the unintended consequence of shifting a crisis from one sector to another, aggravating resource constraints, particularly when adding the pressure of energy and water policies on food systems (Rasul 2016). For example, by subsidizing water for irrigation, leading to inefficient water uses and high energy costs, increasing dependability on energy prices. Many technologies being developed show questionable trade-offs between energy and water supply, such as desalination or some forms of modern irrigation (Pittock 2011). Furthermore, energy and climate change policies, especially mitigation ones, include some water intensive technologies, which have the potential to exacerbate negative trade-offs between water and energy, clear examples of this are hydraulic fracturing or carbon capture and storage (CCS) technologies which use large quantities of water and can lead to contamination (Stillwell et al. 2011).

The thesis applies novel approaches to investigate how these fields interact with one another, rather than simply looking at them as independent systems. The multidisciplinary 'system-of-systems' approach has emerged as an important development, recognising the need for more collaborative infrastructure design and policy development (Crossley 2010).

Addressing issues of water and energy in the context of a changing climate will require better and integrated policy frameworks and institutional settings to prioritize key issues. Many water and wastewater utilities are starting to make investments and management decisions to reduce the energy use of their systems and increase overall efficiency. However, in a 2011 review of research carried out on energy and water interactions, Rothausen & Conway (2011) argued that in the academic literature there is little understanding of the specific energy-water interdependencies in water systems, and a lack of standardized methodologies. This has contributed to the lack of cross-sectoral policies necessary for more resilient and adaptable societies. They suggest that greater integration would allow the water industry to take advantage from more detailed studies, which can help provide targeted material to inform how energy consumption might be reduced. Thus, understanding and quantifying the energy use of water systems is crucial for evaluating where the largest efficiency gains can be made by the water sector, and diminish negative trade-offs.

One way in which the energy consumption of sectors is evaluated is through the calculation of Energy Intensity. Energy intensity (kWh/m3), also known as embodied energy, is the total amount of energy, calculated on a whole-system basis, required for the use of a given amount of water in a specific location (Wilkinson 2000). It is a useful metric to evaluate the specific amount of energy required to treat/manage a unit of water. In the water sector, energy intensity usually represents mostly electricity consumption, as electricity typically represents over 90% of the energy used in this sector. Unless specified otherwise, when the term energy is used throughout the thesis it can be assumed to mean mostly or solely electricity use. Similarly, while in the water sector water use and water consumption carry wholly different meanings, energy use and consumption are used almost interchangeably throughout the thesis.

Some work has been done to quantify the energy costs of water infrastructure systems. Kajenthira et al. (2012) have estimated the energy requirements for different stages of the water system in Saudi Arabia. Through modelling the water requirements of several population centres, they estimated the energy intensity of water infrastructure system (0.70-2.20 kWh/m3), and found that both, water and energy could be saved by increasing wastewater reuse and reducing the use of desalination and groundwater. Cook et al. (2012) carried out an analysis of energy use in the urban water sector in Australia. They estimated that the energy intensity of water supply is around 0.65 kWh/m3. They compared two periods of time and found an increase in the energy intensity over time. They also try to explain trends and energy consumption in wastewater, observing an intensification of the system. Other similar energy in water quantification studies have been carried out for specific geographic regions, including Kenway et al. (2008) in South East Queensland, Bennett and Park (2010) in California, Stillwell et al. (2011) in Texas, Hu et al. (2013) in Beijing and Nogueira Vilanova and Perrella Balestieri (2015) in Brazil, many of which are the first attempts to understand the way in which regional water infrastructure systems consume energy.

There has been no comparable research study carried out for any area, or region, in the UK. This is despite the energy consumption of the sector increasing in the last decade. This is showcased by a comparison between the figures reported in the Water UK Sustainability of the Sector Reports (Water UK 2006-12), which show that the electricity consumption of the sector has increased by over 10% in 8 years (from 8160 GWh consumed in 2002/03, to 9016 GWh in 2010/11), with water delivery numbers remaining roughly the same.

Furthermore, there have been no studies integrating detailed energy costs into short or long-term water resources planning. Having a detailed understanding of the energy patterns of current water systems can help to inform water resources planning, and support more integrated decision-making processes. Water resource planning is widely regarded as a problem of decision making under uncertainty. The planning problem is conventionally framed as one of selecting least cost options to achieve the desired security of supply. However, whilst energy costs usually represent the first or second greatest operational cost of a water utility (after staff costs) the changing nature of energy use in water resource systems has not been quantified, on a sound empirical basis, in past calculations.

To reduce uncertainty about specific water and energy linkages, and to develop transferable models, new, more focused approaches to assessing these relationships are required. This includes the delivery of empirically-based estimates that can accurately represent interdependencies. As long as energy use figures are modelled from water use estimates and vice versa, there will be large implicit uncertainties. There is currently little, or no, publicly available information for studying how energy is used for water and wastewater management in the UK and globally. This is coupled with little understanding of what it is used for and by whom it is used. Information about energy consumption is usually highly aggregated, over time and uses. Therefore, the potential to inform decision-making to drive efficiency has been very limited. To address this, the thesis investigates the connections between energy and water, in the context of climate change, and the challenges that this relationship presents for sustainable development. It is argued that widening the perspective from water-related energy in the supply system, to water-related energy in the wider water use system, offers greater scope for system-wide options to reduce energy consumption and increase efficiency.

Four clear novel contributions are made by the thesis, two empirical and two methodological. Empirically, the thesis provides the first instance of Energy Intensity figures for the UK and gives evidence of the effects of changing technology in wastewater treatment. Methodologically, the thesis provides the first example of including energy as a main decision-making element in water resources operation and planning and provides a methodological approach to use energy costs to find inefficiencies in systems and areas for investment.

1.2 Aims and objectives

The doctoral thesis aims to *evaluate the use of energy in water infrastructure systems and introduce a quantitative approach to understanding current and future relationships*. The research aims to inform planning and policy making to facilitate more efficient and sustainable water infrastructure systems. The project has been developed in collaboration with Thames Water, England's largest water utility. Thus, it is based on real data that provides useful insights for a range of academic, industrial and governmental stakeholders.

Contributing to the main aim the thesis is structured around three main objectives:

1. Identify, map and quantify the energy consumption patterns and energy intensity of water and wastewater infrastructure systems.
2. Develop a methodological approach to incorporate detailed energy costs into water and wastewater resource planning decisions.
3. Evaluate energy implications of alternative management strategies and technological investments to inform policy development and decision-making for more sustainable systems.

1.3 Outline of thesis and research methods

To address the aim and objectives, the thesis encompasses a variety of methodological approaches appropriate to tackling each objective. Chapter 2 provides a literature review that underpins the theoretical and methodological development of the thesis. Chapter 3 addresses the first objective, while Chapters 4-6 address specific elements of Objectives 2 and 3. Chapter 4 focuses on long-term management strategies for water resources planning, Chapter 6 focuses on short-term technological investments for water supply, and Chapter 5 addresses objectives 2 and 3 from a wastewater resources perspective. The Thames Region water and wastewater management system is used to illustrate the methods applied for investigation. Table 1-1 shows the thesis rationale and how the chapters fit together to contribute to the overall aim, which is followed by a more in-depth discussion of each chapter. Thus, a combination of empirical and simulation modelling is used.

Table 1-1: Rationale for thesis structure

<table>
<tr><td colspan="3">Aim: evaluate the use of energy in water infrastructure systems and introduce a quantitative approach to understanding current and future relationships</td></tr>
<tr><td>Energy-water Interdependencies</td><td>Water resources</td><td>Wastewater Resources</td></tr>
<tr><td>Present-day</td><td colspan="2" align="center">Chapter 3</td></tr>
<tr><td>Long-term</td><td>Chapter 4</td><td rowspan="2">Chapter 5</td></tr>
<tr><td>Short-term</td><td>Chapter 6</td></tr>
</table>

Chapter 3 presents a systems-perspective methodological approach using empirical modelling and statistical analysis to investigate the energy consumption patterns in water and wastewater infrastructure. The chapter provides a detailed understanding of the drivers of energy consumption and identifies hot spots of energy intensity that can help inform water utilities in making decisions to improve efficiency, using the Thames system as a case study. An important contribution of the chapter is the provision of Energy Intensities for each functional component of the water use cycle in the UK. The findings of this chapter form the basis of the more detailed examinations in subsequent chapters.

Chapter 4 responds to the challenges in objectives 2 and 3 by presenting a methodology and analysis for incorporating detailed energy costs into long-term water resources planning and decision-making. A model is presented that represents the detailed water and energy interactions in water infrastructure systems and projects energy consumption over a long-term planning period, including uncertainty from the effects of climate change, population and water demand changes. This paper uses a novel methodological approach, Robust Decision Making (RDM), described in Chapter 2, coupled with multi-objective optimization, and demonstrates how the model can be used to inform the choice between alternative water management strategies, and to assess trade-offs between energy costs and water supply security. Thus, Chapter 4 successfully addresses energy-sensitive water resources planning within a long-term framework.

Chapter 5 also responds to objectives 2 and 3, but focused on wastewater resources. The chapter focuses on wastewater management and builds on the findings of Chapter 3 to quantify the relationship between wastewater infrastructure systems, energy and changing effluent quality standards, using a regression-based model. The findings of Chapter 5 can aid water utilities to make energy-sensitive wastewater management decisions within the context of changing regulations in the short and long-term.

Chapter 6 presents a methodological approach to assessing short-term investment decisions in a water supply network, by applying linear optimization, in combination with a multi-objective optimization Genetic Algorithm, to a water pumping and clean water treatment infrastructure network. While Chapter 4 focuses on robust long-term strategic system water management options, this chapter supplements the investigation by focusing on short-term energy efficiency improvements in existing infrastructure, and uses the London water supply area to demonstrate the robust optimization methodological approach proposed.

As can be noted, to meet each objective, a fundamentally different methodological approach was needed: current relationships between energy and water systems lend themselves to empirical and statistical analysis, while future relationship assessments require the use of simulation modelling. As such, an overarching methodological chapter was not deemed appropriate, as each chapter addresses the methodological approach taken to address its aim in detail. The thesis is unified through the complementarity of the chapters in addressing the overall thesis aim, rather than by one encompassing methodological approach.

Chapter 7 presents the conclusions of the thesis and shows how the results of each chapter contribute to answering the overarching aim. A summary of the main findings is presented, while highlighting their applicability. The thesis ends with a short roadmap for future work in this area.

2. Methodological framework

2.1 Measuring the energy use by water utilities

The energy use of water infrastructure systems has been analysed widely in recent years from various perspectives. Energy is required to operate all stages of the water cycle, which include water abstraction, treatment, pumping and wastewater collection and treatment. However, many studies have focused on aggregate numbers, only on the water delivery section of the water use cycle (Spang and Loge 2015); or on a specific stage of the cycle, such as water distribution (Bolognesi et al. 2014), water treatment (Bonton et al. 2012) or wastewater treatment (Nowak, Enderle, and Varbanov 2015; Chae and Kang 2013).

Few studies have tried to understand the energy consumption of water delivery, treatment and wastewater collection and treatment at a system level. Many of those that have (Kenway et al. 2008; Stillwell et al. 2011; Bennett and Park 2010; Nogueira Vilanova and Perrella Balestieri 2015; Hu et al. 2013) have based their assessments on geographically specific case studies (Kenway in South East Queensland, Bennett in California, Stillwell in Texas, Nogueira in Brazil and Hu in Beijing). This is because the study of energy and water interdependencies is strongly influenced by the local infrastructure, geospatial and cultural characteristics of a region.

The water sector is relatively energy intensive - according to Watson & Rai (2013) it is the fourth most energy intensive sector in the UK, consuming 3% of total energy demand - and also highly sensitive to climate change. Current electricity prices are around £0.085/kWh, and are projected to increase to approximately £0.13/kWh by 2035 according to the DECC Energy & Emissions forecasts for electricity prices (£/kWh - central industrial sector) (DECC 2014; DECC 2015a). Thus, reductions in energy intensity and substitution in sources of energy - where self-generation is financially efficient and possible- are of interest to water utilities. *Energy intensity* (kWh/m^3), also known as *embodied energy*, is the total amount of energy, calculated on a whole-system basis, required for the use of a given amount of water in a specific location (Wilkinson 2000). Models for the South East of England project rising temperatures, wetter winters, drier summers, more intense rainfall events and greater climate variability (Baleta and Mcdonnell 2012). This is likely to translate into higher water demand, more widespread water stress with increased risk of drought, potential raw water-quality problems, increased need for storage and transport, as well as more extreme downpours with a higher risk of flooding. Government policy for energy and water is typically thought about in silos, which can result in policy fragmentation and a misalignment of incentives (Napoli and Garcia-Tellez 2016). Thus, a systematic approach for conducting further inquiry into the energy drivers that produce observed ranges of energy intensity (kWh/m^3) can aid in bridging the understanding of energy use patterns for the water sector; which can in turn help to contribute to the development of government policy. Energy intensity has been previously used successfully as a functional unit to evaluate the environmental impact of water infrastructure systems (including both water delivery and wastewater treatment) and highlighting where potential opportunities lie within the system (Mahgoub et al. 2010; Lundie, Peters, and Beavis 2004).

Napoli & Garcia-Tellez (2016) found that estimating water-related energy costs at a national level can be misleading, to the extent that it may limit the ability to improve the energy efficiency of water delivery. This is because, even if there may be resources available in a country, they may not be readily available for the population. This is the case in the UK, which is generally considered to be a water abundant country, yet much of the country's population and agricultural activity is found further south, where water resources are relatively scarce. Similar studies have been carried out for other regions, such as California and Australia, finding more regionally relevant energy-water relationships (Kajenthira, Siddiqi, and Anadon 2012; Cook, Hall, and Gregory 2012; Spang and Loge 2015). Its regional approach is thus appropriate, considering that although water policies are driven by a national framework, the South East of England has some of the largest population growth and already suffers from water scarcity.

Studies that have aimed to estimate energy use throughout the water use cycle tend to come up with varying and distinctive results. The energy demands of different sections of the water cycle depend on the location, geography, climate, availability and quality of water, and treatment and disposal of sewage. Some of the usually higher elements of energy demand include pumping water from distant or deep sources; distributing water over wide areas, asset conditions, and pipe leakage; treatment of sewage by aeration and pumping raw and treated effluents (Caffoor 2008). Globally, energy is always among the top three cost items to water utilities, often coming second after labour costs (Barry 2007). In the Thames Water catchment area, in the South East of England, it is the largest operational cost. In developing countries, energy is usually the highest cost associated with water supply. Areas with high population concentrations, especially if there are resource and disposal constraints, are usually the highest consumers, and their consumption will continue to increase (Brandt et al. 2011). On the other hand, end-uses of water (domestic, industrial, agricultural) consist of the highest proportion of energy use in the water use cycle, mostly associated to the heating of water. It requires central attention, as savings in energy and water use on the demand side can have repercussions for energy use throughout water supply. Nonetheless, it has been shown that many inefficiencies occur before water has even reached the end-user (Barry 2007). Thus, even significant modifications in the behaviour and consumption of water will need to be coupled with technological and infrastructure investments to meet our future needs, while taking past infrastructure decisions into account which are often long-lived.

2.2 Methods for water resources planning

Water utilities are responsible for planning and investing to achieve reliable supplies of water in the long-term. Uncertainties abound in water resources management with pressures from climate change, urbanization, population growth and increasing demand (Roach et al. 2016). Water planners and agencies are thus under pressure to make water resources planning decisions that can meet demand while ensuring affordability, and which will be reasonably robust and adaptable to future uncertainties. When investments are needed to enhance security of supply, there is a trade-off between affordability for the customers of the water utility, who ultimately pay for investment via their water bills, and security of supply.

There have been studies that have focused specifically on measuring current energy consumption of water infrastructure systems (Bolognesi et al. 2014; Spang and Loge 2015), with little consideration of uncertainties associated with changing demand and supply options that may be necessary in future (Dubreuil et al. 2013). Hall et al. (2011) carried out a study in South East Queensland, Australia, of the energy consumption (and associated greenhouse gas emissions) for water services looking 50 years into the future. Although they identify uncertainty for emissions factors they did not include uncertainty estimates for population projections, or per capita demand. Their findings suggest that without action the rate of greenhouse gas emissions of the sector is on track to more than double in 50 years under current government policies in Australia, although this does not take into account the decarbonization of the grid.

Traditionally, water infrastructure costs are dealt with in whole life terms; that is, costs are estimated as discounted capital expenditure (CAPEX), as well discounted operational expenditure (OPEX), though the operational costs have tended to be dealt with rather crudely. Given the very different energy implications of alternative planning options, there is a strong case for a more sophisticated treatment for energy costs in decision-making processes. Requirements to consider greenhouse gas emissions associated with energy use in the water sector are further motivating consideration of the energy efficiency of different water resources plans. Developing a further understanding on how energy consumption may look like for water infrastructure systems in the future will provide more insight to the water sector, as it seeks to both to supply more affordable water to customers and to do so in a more sustainable way.

In the UK, water utilities are required by the Environment Agency (the environmental regulatory body), to develop Water Resource Management Plans (WRMP) every 5 years, that outline their long-term strategies for providing a reliable supply to meet demand, using Integrated Water Sources Management (IWRM) approaches (Roach et al. 2016). These plans need to manage the trilemma of water security, affordability and sustainability, three issues which also shape water and energy interdependencies. The plans must cover periods of at least 25 years, and outline and justify any management decisions to augment supplies or to manage demand (Environment Agency 2016).

2.2.1 Decision-making methodologies

There is growing recognition of the need to address uncertainty and its impact on water infrastructure planning (Ray and Brown 2015), which has led to increasing uptake of various methods for decision-analysis under uncertainty including decision scaling (Brown 2011), Information-Gap Decision theory (IGDT) (Ben-Haim 2006; Matrosov, Woods, and Harou 2013) and Robust Decision Making (RDM) (Lempert 2003; Groves et al. 2013).

These approaches emphasize robustness to uncertainty, including climate and other uncertainties, but are slightly different in their approach. Decision-scaling is a methodological approach that develops robustness by using stress tests to identify system vulnerabilities, and then iteratively reduce system vulnerabilities through targeted design modifications. According to Brown (2011) decision-scaling performs well only when historical climate information is available, the impacts of climate change can be quantified and decision makers are strongly involved in the process. IGDT defines robustness as “the maximum uncertainty […] over which a strategy achieves a certain level of performance” (Hall et al.

2012), and focuses on situations with a severe lack of information (Ben-Haim 2006). RDM seeks to identify a plan that performs "reasonably well compared with the alternatives over a wide range of plausible futures" (Lempert et al. 2006). It employs the concept of "exploratory modelling", by using computer models to simulate system response under a wide range of parameter settings (representing future scenarios) that are sampled using Monte Carlo simulation and analysed with post-processing diagnostic tools. Robust strategies are identified by quantifying system performance according to one or more performance metrics, and applying decision rules to identify alternatives that perform acceptably well over the largest possible regions of possibility space. Multi-objective optimization can be applied to evaluate the trade-offs between the multiple performance criteria. According to Ray and Brown (2015), a strength of the RDM methodology is the ability to consider a wide range of climate, socioeconomic and other uncertainties to provide information on how a system may be affected by combinations of these factors.

RDM is a good candidate methodology to integrate detailed information about operational energy as an additional measure of performance of the system (on top of security of supply) under a wide range of possible future states, due to its flexibility to integrate a wide range of uncertainties, and the ability to rank based on multiple performance metrics. For these reasons the thesis uses the RDM methodology, as opposed to similar methodologies like decision-scaling, which focuses more specifically on climate information and IGDT which performs better in situations with a severe lack of information.

The performance criteria typically used in RDM for water resources planning include costs, security of supply and, sometimes, environmental impacts.

Matrosov et al. (2013) also included energy prices as a source of uncertainty in their RDM analysis of water resources management plans in the Thames Water region but then condensed the cost implications into a single whole life cost, rather than considering capital costs and energy costs as two different criteria. Energy costs are usually the second largest operational cost in many water utilities in the UK (after staff costs), and the largest in many other parts of the world. Thus, understanding and exposing the energy implications of infrastructure decisions could help make decisions that avoid locking-in to less sustainable and costly options and support existing decision-making processes.

Addressing these energy implications is fundamental to reduce long-term operational costs and associated greenhouse gas emissions. This thesis uses a coupled systems model of energy use and water infrastructure to better incorporate energy costs into the long-term water resources planning process. The model integrates current understanding of the energy implications of water supply infrastructure systems, applied to a systems-level illustration of the Thames Water system, with the goal of informing the decision-making process. The findings for the case study are presented using the RDM methodology framework in conjunction with a multi-objective optimization. The study provides the first application of a multi-objective RDM approach to a joint water-energy challenge, which focuses specifically on the potential energy implications of water supply options. By expanding beyond both an RDM framework and an optimization framework the study is moving towards integration of the two approaches. This is done by using a genetic algorithm to find the most efficient design modification to improve water system robustness at the lowest energy costs.

2.3 Methods for water system operations

Water supply networks are complex systems that require high investments for their operation. In industrialized nations such as the UK, water infrastructure systems are well established and provide near-universal access to clean water. However, several issues remain, such as the high energy costs associated with their operation, usually in the form of electricity, and high associated greenhouse gas emission costs (M. J. Brandt, Middleton, and Wang 2011). According to Farmani et al. (2007) water distribution and treatment network investment appraisals traditionally accounted for capital expenditure (CAPEX) and did not adequately consider impacts on operational costs.

Furthermore, growing populations, changing electricity prices and climate change impacts are placing additional strains on existing systems to provide more, better quality water without increasing associated costs. The supply systems require updating and adaptation to changing circumstances, but there are few options available to utilities, particularly those that operate in large urban networks with legacy systems. There is usually little room to build new infrastructure and invest in large projects. The main options to improve the operational costs of existing water pumping and treatment networks usually include: (1) improve distribution pumping efficiency, (2) upgrade technologies in water treatment plants or (3) increase capacity at more efficient works.

In existing networks, it is costly to add new pipelines and other physical assets, particularly in heavily urbanized areas. However, operational changes and strategic technology upgrades can significantly reduce costs. Optimization methods can be employed to address the rising energy consumption in large urban water supply systems (Puleo et al. 2014). Optimization techniques have been used extensively to study water network design in the past. In particular, there has been a large focus on optimizing variable speed pumps and the cost savings from multi-pattern electric tariffs (Ulanicki and Kennedy 1994; Sarbu 2016; Broad, Maier, and Dandy 2010; Schaake and Lai 1969; Perelman, Housh, and Ostfeld 2013; Ghaddar et al. 2015). However, optimization for the operation of networks has not received as much attention, but offers significant opportunities for cost reduction (Ulanicki and Kennedy 1994). The significant energy consumption in water treatment works offers opportunities to focus on treatment systems that could provide larger savings. Particularly lacking has been the use of real-world applications instead of theoretical networks, which has limited the uptake in industry (H. R. Maier et al. 2014; H. Maier et al. 2015)

The water supply system includes abstraction and water treatment works as well as the pressurized distribution system. In this study, all the key segments of the supply system are assessed, and not just pumping and distribution that has often been the focus in past work (Kougias and Theodossiou 2013; Puleo et al. 2014; Hashemi, Tabesh, and Ataeekia 2013). Optimizing water supply networks as a system can enable a more holistic view of the energy consumption hotspots, and can offer a wider variety of options to choose from when it comes to increasing energy efficiency. For example, by calculating the savings of re-routing water to the most efficient treatment works, or through evaluating the whole-system cost benefits of small capital investments. Utilities usually approach energy costs for the company as a whole, and thus addressing energy hotspots at whole system level can provide an indication of the best opportunities, company-wide, to save costs, rather than focusing on just pumping or treatment work savings which may miss larger savings.

2.3.1 Multi-objective optimization

The most popular mathematical modelling and programming techniques for water network design and operation have conventionally included Linear Programming (LP), Dynamic Programming (DP) and Non-Linear Programming (NLP) (Md. Azamathulla et al. 2008). Linear Programming has been used widely to represent water networks. Many networks include non-linear relationships, however, LPs have been found to produce good approximations (Hsu and Cheng 2002; Puleo et al. 2014).

Traditionally, the design and operation of water networks has been seen as a single-objective, least-cost optimization problem with a focus on pipe sizing and diameters (Marques et al. 2012). In the last twenty years, there has been an increasing focus on techniques that include Evolutionary Algorithms (EA), particularly, Genetic Algorithms (GA) to optimize water networks. An in-depth assessment of the state-of the art of evolutionary multi-objective optimization techniques used for water resources is given by Reed et al. (2013). GAs have been defined as 'search algorithms that are based on the mechanism of natural selection and natural genetics' (Forrest 1993; Man, Tang, and Kwong 1996). Genetic Algorithms (and other heuristics-based non-linear optimization methods) offer advantages such as random search capabilities, but do not have a mathematical basis for guaranteeing the discovery of the global optimal solution. Furthermore, GAs are computationally expensive and require computing resources and run-time. Linear optimization and other approaches are often desired because the solution is guaranteed to be optimal (however, many real-world problems do not lend themselves to neat LP formulations). Thus, while GAs are widely used, it is also important to keep their limitations in perspective, such as the long computational time they require. GAs has been applied to a variety of water resources problems (Wardlaw and Sharif 1999), such as groundwater issues (Hilton and Culver 2005); or water distribution network problems. Chapter 6 integrates the representation of a water supply system in a linear program fashion with a Multi-Objective Evolutionary Algorithm (MOEA) to evaluate trade-offs between a set of investments in a hybrid model.

Cherchi et al. (2015) recently argued that there is a need for multi-objective analysis and optimization in the reduction of energy in the water sector, but this remains poorly investigated, and tools for integrated system planning and operation are not widely available. Chapter 6 develops a simplified network model of a water supply system and applies linear optimization to find an optimal routing of water through the network to reduce energy consumption. Then, a MOEA is applied to the optimal network to evaluate further gains that can be achieved from small capital investments at the bottlenecks in the network. The bottlenecks in the network are identified through an analysis of the Lagrange multipliers from the LP. Using GAs on complex water systems can be computationally intensive. Thus, there is a need to increase the computational efficiency of water network models in order to facilitate their use in the sector (Broad, Maier, and Dandy 2010). One way to achieve this is via network simplification, which can limit its applicability, but reduces running times and can inform water utilities in their decision-making processes.

2.3.2 Incorporation of uncertainty

Previous studies have focused on deterministic approaches to optimizing both the design and operation of water networks (Perelman, Housh, and Ostfeld 2013), thus providing limited applicability to real-world network where there is usually uncertainty in the data and parameters. Recent studies have highlighted that uncertainty in model parameters has very rarely been incorporated into water network optimization studies (D'Ambrosio et al. 2015). A very recent review of optimisation methods in water resources called for the incorporation of uncertainty into operational optimisation of water distribution networks as one of the main future research challenges facing the field (Mala-Jetmarova, Sultanova, and Savic 2017). In Chapter 6, the methodological approach quantifies uncertainties by incorporating a Monte Carlo simulation analysis.

An uncertainty analysis also becomes more important when greenhouse gas emissions associated to energy costs are considered. GHG emissions are externalities that can increase risks to water companies. Water utilities are large contributors to GHG emissions and usually contribute to national emissions reduction targets, for example as set out in the UK Climate Change Act. Thus, as the importance of reducing greenhouse gas emissions in the water sector increases, so does the need to understand where they come from and how to reduce them.

Menke et al. (2017) recently carried out a multi-objective optimization to reduce electricity costs and GHG emissions in water network pump scheduling. They found that taking greenhouse gas (GHG) emissions into account in the optimization provided significant benefits for decision-making. They also note that their study has only focused on the scheduling of pumps, but studies that focus on optimizing the operation of pumps, reservoirs and water transmission mains as a whole network are needed, particularly those that consider elements such as GHG emissions associated with the operation of the network. Chapter 6 utilises the MOEA to evaluate the trade-offs between CAPEX and OPEX (in the form of electricity consumption), and their associated GHG costs.

In this thesis, a multi-objective optimization approach is developed to identify options for reducing operational costs through energy consumption minimization, and the approach is applied for London's water supply network. The results are discussed in the wider context of how the energy consumption and associated greenhouse gas footprint of existing water supply systems in large urban metropolises can be improved with strategic investments.

2.4 Data sources

The majority of data used throughout this thesis was provided by Thames Water in the form of operational datasets. These included the electricity consumption (kWh/month), water flows (ML/d) (for the period between September 2009 and September 2014) and wastewater flows (m^3/d) (from January 2011-December 2014). Other datasets included the geospatial information for the infrastructure assets, monthly reported leakage (Ml/d) and monthly distributable input (Ml/d) for the same sample period (Table 2-1).

Table 2-1. Datasets used for the study, including name, unit, period covered, granularity

N	Dataset name	Unit	Period Covered	Granularity	Further Details
1	Electricity Consumption for Thames Water Utility	kWh/m	Sept-09: Sept-14	Monthly total values	506 Large Assets and 3224 Small assets (all electricity consuming assets)
2	Water Flow	Ml/d	Nov-09: Oct-14	Monthly averages	98 assets (treatment works)
3	Wastewater	m^3/d	Jan-11: Dec-14	Daily totals	257 assets (wastewater treatment works)
4	Geospatial information	x, y coordinates	n/a	n/a	1793 assets (many assets are located in the same area thus fewer x, y coordinates)
5	Technologies present in water assets	Yes or no	n/a	n/a	Presence or absence of 16 technologies at 98 assets
6	Monthly Reported Leakage	Ml/d	Apr 1996-Dec 2014	Monthly averages	System level
7	Monthly Distributable Input	Ml/d	Apr 1996-Mar 2014	Monthly averages	System level

For Chapter 5 on wastewater, Thames Water provided additional details on the monthly incoming and outgoing concentration (mg/l) for Biochemical Oxygen Demand (BOD), Ammoniacal Nitrogen (NH_3-N), Suspended Solids (SSs) and Chemical Oxygen Demand (COD) for six large WWTWs in London for the period of January 2011 to December 2014. During this period, a series of upgrades were commissioned in four of the plants. Details about upgrades to the

WWTWs to meet more stringent effluent standards were also received: inlets to increase the flows passed to treatment (more treatment streams, more/larger pumping stations, as well as inlet works expansions); additional primary settlement tanks (PSTs), additional Activated Sludge Processes (ASPs) and final settlement tanks (FSTs) as well as the percentage of flow these upgrades would treat, and when they were installed.

3. Watts of water: understanding energy consumption patterns in water infrastructure systems using a case study in the South East of England

3.1 Introduction

Water delivery and management consume significant amounts of energy, mostly in the form of electricity. This energy is required to operate all stages of the water cycle, which include water abstraction, treatment, pumping, wastewater collection and treatment. This chapter applies a systems approach to examining energy consumption patterns in the Thames Water catchment. Current analyses of the energy consumption of water systems report aggregated, system-wide, usually annual numbers, which can miss significant differences in space and time. Using a disaggregated approach, we show how breaking down the system into components, in combination with a system view, can yield hot spots of energy intensity in the system, whilst at the same time understanding the contributions that local factors make to overall energy demand. The approach identifies several areas to focus on in the management of water resources to reduce energy intensity, for example: clean water treatment is shown to be more energy intensive and to consume more energy overall than wastewater treatment. There are also differences in the geospatial energy intensity of water infrastructure systems. The study also describes a framework for other utilities in the UK to explore the patterns of energy consumption in their areas and provides benchmark energy intensity figures that can be used for other studies.

The chapter provides an analysis of energy use and intensity to aid in the understanding of water management, for example, energy efficiency programmes, and helping to prioritize high potential system opportunities. To do this, a components approach is applied to examining energy consumption patterns in a water infrastructure system. Current aggregated approaches on the energy consumption of water systems report large, system-wide, usually annual numbers, which can miss significant differences. Using a disaggregated approach, we show how breaking down the system into components, such as specific region, in combination with a system view, can yield hot spots of Energy Intensity (EI) in different sections of the system. This could enable targeted efforts on energy efficiency or energy substitution, and allow for more economic and sustainable ways of delivering water to customers.

A similar methodological approach has been applied to a water utility in California by Spang & Loge (2015), although focusing only on water treatment and delivery. They found geographically relevant variations in the EI of water delivery, resulting from seasonal and topographic effects. Similarly, this chapter identifies several areas which could help to reduce the EI of water management. These include the patterns of energy consumption of water and wastewater treatment, as well as an influence from the geospatial location of the infrastructure on EI. These influences are quantified and explained.

The focus is on direct consumption of electricity in the system, which is that consumed by the operational phase. Previous studies have found that direct consumption accounts for the largest proportion of electricity use, upwards of 87% (Parsons and Marcet, 2012). Marsh (2008) found that 'significant reductions in energy consumption may be gained by focusing on the direct electricity consumption in the water sector'. Life-cycle studies have shown that electricity consumption in the operation phase is generally the most important factor affecting environmental performance indicators in water treatment systems (Vince et al. 2008; Mahgoub et al. 2010; Amores et al. 2013). Energy consumption is a good indicator of the environmental burden of water infrastructure systems (Amores et al. 2013). Furthermore, this chapter includes only operational and not construction and phase-out of infrastructure, which has been indicated to be negligible when compared to the operation phase (Environment Agency 2008a; Ortiz, Raluy, and Serra 2007). This work is the first case in a British context that includes all stages of the water infrastructure system, as well as site specific and seasonal variations. Particularly, using operational data in a large urban area the study aims to provide a more detailed explanation of energy use.

The structure of the chapter is as follows: first, the case study region is presented, followed by the methodological approach taken and datasets used. An overview of energy in water in the specific case study system is given, providing a geographical and systemic context. This is followed by the methodological analysis of the system, providing insight into the drivers of energy consumption across all stages of the system. The chapter concludes with a discussion of the results, observations and conclusions.

3.2 Materials and methods

This study calculates the Energy Intensity (EI) (kWh/m^3) of the system by dividing the total energy used by each stage: water pumping, which includes pumping of raw water (water networks) and pumping of pressurized clean water (operational control), water treatment, wastewater networks and wastewater treatment, by their corresponding water flows. End-uses of water were out of the scope of this study. The datasets used are outlined in section 2.4 of the thesis.

3.2.1 Methodological approach

Once the datasets were matched with their corresponding variables, the analysis of the system-wide energy use (kWh) was performed. The EI was calculated, for each month, by dividing the corresponding energy values of the system, with its corresponding water or wastewater flow (1-4). EI is defined as the energy, in kWh, needed to treat one meter cubed (m^3) of water. The equations are normalised to capture the electricity consumed per unit of water and wastewater, making them comparable, and are as follows:

$$EI_{pumping}\ [kWh/m^3] = [(\text{Water Pumping } [kWh]) / (\text{Water Flow } [m^3])] \quad (1)$$

$$EI_{water}\ [kWh/m^3] = [(\text{Water Treatment } [kWh]) / (\text{Water Flow } [m^3])] \quad (2)$$

$$EI_{network}\ [kWh/m^3] = [(\text{Waste Network } [kWh]) / (\text{Wastewater Flow } [m^3])] \quad (3)$$

$$EI_{waste}\ [kWh/m^3] = [(\text{Wastewater Treatment } [kWh]) / (\text{Wastewater Flow } [m^3])] \quad (4)$$

The analysis was divided into: water pumping (includes pumping of raw water, water networks, and clean water, operational control), water treatment, wastewater networks (collection and conveyance of sewage) and wastewater treatment. Functional component is the term used to describe the sub-segments, or stages, of the water use cycle (Bennett, Park, and Wilkinson 2010). The objective was to develop an understanding of energy use and water/wastewater flow trends in each functional component, and present a range of energy consumption and EIs:

1. **As a complete system** - to obtain an aggregated snapshot perspective

2. **By functional component** – to understand differences across stages of the water infrastructure cycle
3. **By Water Resource Zone** - allows for geographical visualization

3.2.1.1 Complete system and functional components

To calculate the complete system energy use, the electricity consumption data was used. The aggregated EI of the system was calculated by adding the EIs of each system-wide functional component using the equations (1-4) above, as has been done in similar studies.

3.2.1.2 Water Resource Zones

The division of EI by geographical location may aid in understanding where reductions or substitutions in energy consumption may be most useful to water utilities; and where, for example, targeted programs for water and energy efficiency may be most useful, or where energy substitution may be more cost-effective. Thus, the EI of the system was calculated by WRZ and is visualized in the results section. The water EI was calculated by using the total average of the monthly energy consumption of assets in each WRZ over a period of 36 months (3 years), and dividing it by the average monthly water flow through each corresponding asset in each WRZ. The category 'other' includes assets located outside the WRZs which Thames Water is also using to supply water and pump water into its system.

3.2.2 The study area

The case study system is in the south east of England, principally the area serviced by Thames Water Utilities Ltd, for clean water supply and wastewater collection and treatment. This area extends from Cirencester in the west to the eastern side of London (Figure 3-1).

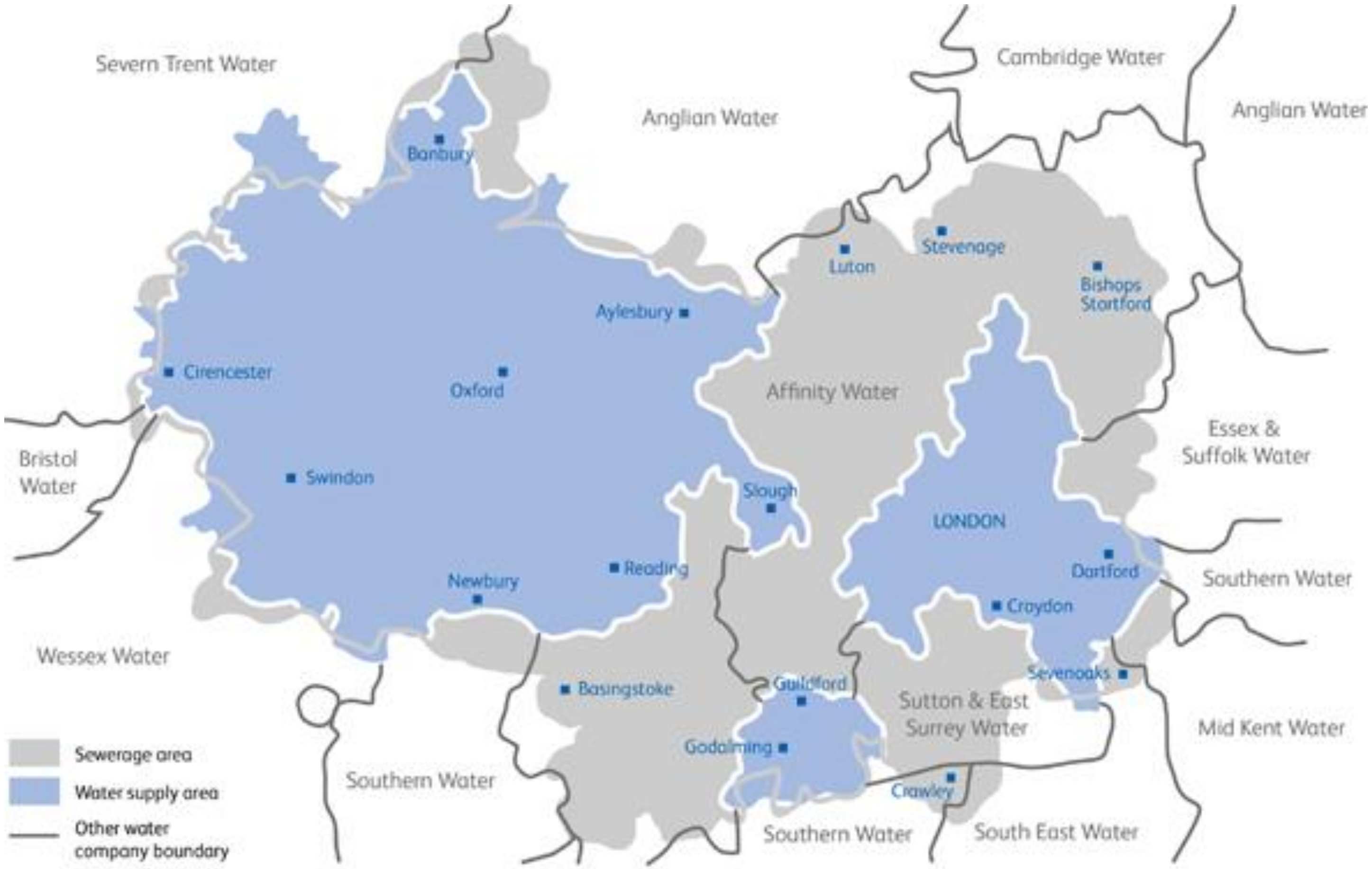

Figure 3-1: Thames Water sewerage and clean water supply area map (Thames Water 2016c)

Thames Water is the UK's largest water and wastewater Service Company, covering approximately 15 million customers in London and the South East of England. They operate 102 water treatment works, 26 raw water reservoirs, where most of the water is stored, 288 pumping stations and 235 clean water service reservoirs, as well as 350 sewage works, two sludge-powered generators, 7 Thermal Hydrolysis Plants, 24 Combined Heat and Power (CHP) plants, 43 solar PV installations and 2 wind turbines (Thames Water 2016b). Thames Water provides water to the drainage basin of the River Thames, but takes its source water from a range of rivers and groundwater sources. The area covered by Thames Water for sewage management is larger than the water supply area. Most of this area, particularly in London, is served by a combined sewerage system, which collects sewage from the end-users as well as rainwater run-off, known as storm water.

The Thames Water supply area is divided into six Water Resource Zones (WRZ). A WRZ is the standard geographical unit for water resources planning and is defined by the Environment Agency (2009) as: "The largest possible zone in which all resources, including external transfers, can be shared and hence the zone in which all customers experience the same risk of supply failure from a resource shortfall." The largest of these in the Thames Region is London, which covers the Greater London area, followed by Swindon and Oxfordshire (SWOX). The water resources for both zones are largely based on abstraction from the River Thames, which is stored in reservoirs. The other zones to the west of London are Kennet Valley, including Reading and Newbury; Henley; Slough/Wycombe/Aylesbury (SWA) and Guildford. These four zones are largely reliant on groundwater abstraction although there are significant abstractions from local rivers, mainly the River Kennet in Reading and the River Wey near Guildford. Overall, existing supply is around 77% from surface water (rivers) and 23% from groundwater (aquifers) (Thames Water 2014b). The WRZs outside London are collectively referred to as the 'Thames Valley'.

For this study, the system is looked at both at a whole system level (whole sewage area for wastewater), and by WRZs (both for water and wastewater), to ascertain similarities and differences between areas, and to understand the flows of energy and water within the system. The London and SWOX WRZs are also further subdivided into their main three zones each to understand variability.

3.3 Results

The results are divided into three sections by: total system variance, variance over time, and geographically (WRZ). The total electricity consumption for the sample system shows that the case study system consumed approximately 3280 GWh in the sample period (of approximately 4 years) to deliver a total of approximately 2,450,000 m^3 a day, and treat approximately 3,400,000 m^3 a day of wastewater. The percentage electricity consumption for each functional component was: 36.18% for water treatment, 0.06% for water networks, 12.91% for operational control, 17.45% for the waste networks, 31.81% for wastewater treatment, and the remaining 1.59% for maintenance, properties, facilities and laboratories. This remaining energy consumption was negligible in comparison to energy consumed by the large functional components, and was excluded from the rest of the study.

The overall system-wide energy intensity for the four largest functional components was 0.437 kwh/m^3 for water treatment, 0.118 kwh/m^3 for operational control, 0.073 kwh/m^3 for the waste networks and 0.267 kwh/m^3 for wastewater treatment. This results in a system-wide average energy intensity of 0.895 kwh/m^3. The study has found that there is a large variability in the system though, and thus average numbers should be understood in a wider context of influencing factors and variability, which this assessment attempts to shed light on. These results could be partially applicable to other regions in the country, but with different levels of urbanization, water quality, system configurations and other local influencing factors operational averages could be dissimilar, perhaps with lower pumping or treatment energy requirements. However, the results are useful because they provide the first benchmark average values for the UK.

3.3.1 Over time

The amount of water delivered over the sample period is mostly constant, whilst the wastewater has significant seasonality due to the storm water infiltrating combined sewers during precipitation events. Figure 3-2(a) shows the corresponding stacked energy consumption of the main functional components over the sample period. There is an increase in energy use between the 2012 and 2013 years in the electricity use of the whole of the system, driven mostly by wastewater treatment. A seasonality pattern can be observed in the data, which could be associated with seasonal demand changes, or climatic variables such as precipitation and temperature changes.

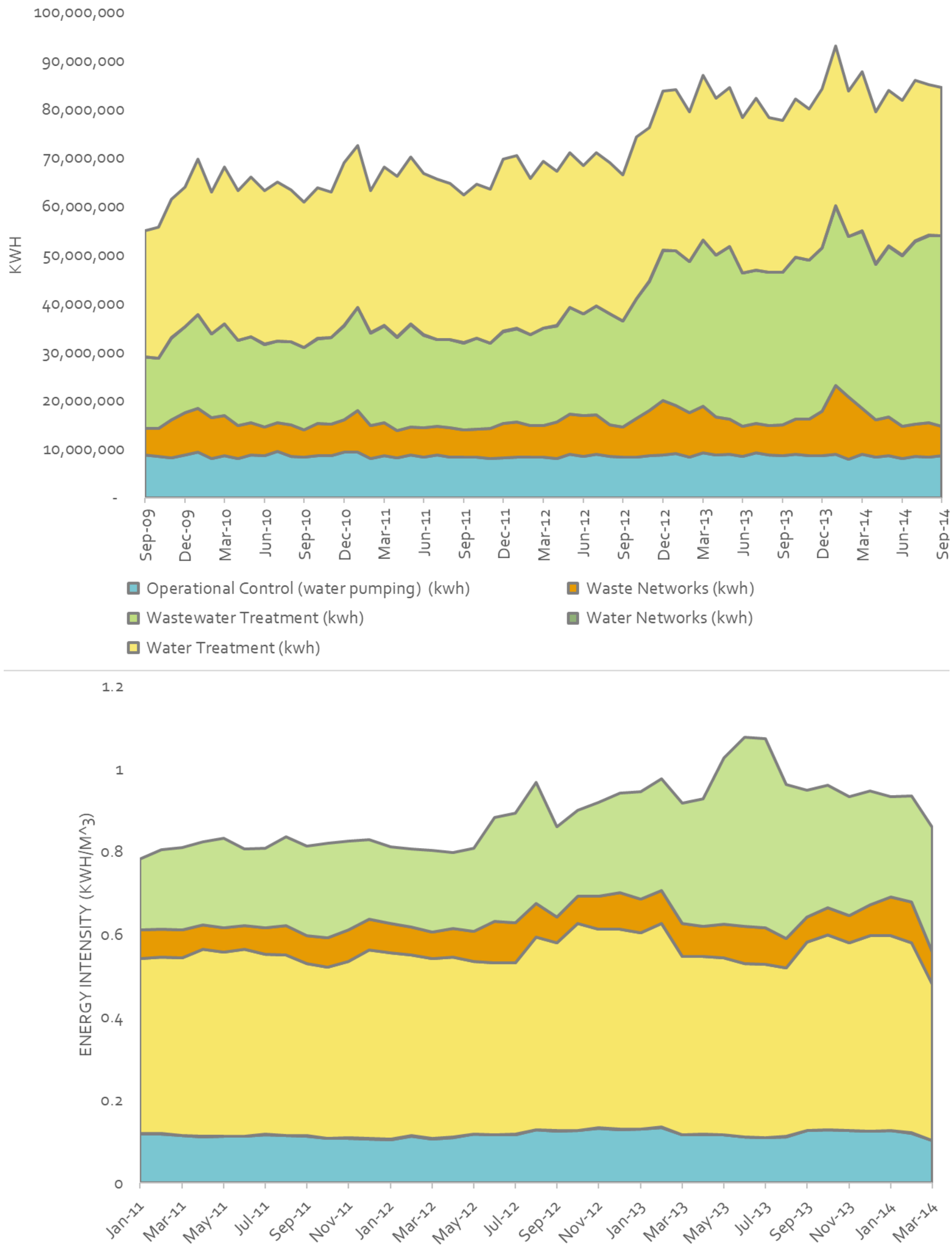

Figure 3-2: Stacked functional components for the case study system over time: (a) by total kWh (b) by Energy Intensity (kwh/m3)

Figure 3-2(a) shows total energy consumption over time, showing that the largest increase in energy use in the sample comes from wastewater treatment. There is seasonal variation, due to weather and other types of event (such as the Olympics in 2012), in the amount of wastewater treated, but no large increase in the amount being treated from the beginning to the end of the sample period. If the energy data is observed closely, the large increase in the energy use in wastewater treatment can be directly attributed to the expansion of five of the largest treatment works in the region, to deal with higher effluent standards. These expansions included 12 new aeration plants, two picket fence thickeners; two activated sludge thickeners to handle surplus activated sludge, 24 additional final settlement tanks, five primary settlement tanks and two new inlet pumps across the five treatment works, which has also increased the capacity to collect and treat more wastewater, and to a better quality. The most significant contribution to the observed increase in energy consumption was associated with wastewater being treated to higher levels of quality rather than any increase in a flow to be treated. This can be normalized by removing the five treatment works that have been expanded over the sample period.

As can be seen, water treatment and wastewater treatment are the largest users of energy within the system. However, this may not mean they are the most intense per unit of water. Thus, the system is also visualized by EI over time. Figure 3-2(b) shows the overall system-wide EI for the five largest functional components over time. Energy is shown ‘normalised’ per unit of water. The stacked kWh used per unit of water in the functional components are shown as a contribution to the total EI, over time. There is less variability as EI is a per unit measure. Both the EI of wastewater treatment, and its total energy use, increased over the sample period. This suggests that the addition of more technologies at the expanded treatment works has led to more electricity being used per unit of wastewater treated. The waste network EI remained relatively stable, as opposed to its total energy use which has a marked seasonality whilst the EI of water pumping remains constant over time. For the sample period, water treatment is the most intense component of the system. The data highlighted a clear seasonal variability. Further studies could compare this seasonality against several climate variables to ascertain if the system intensity changes with these variables.

3.3.2 WRZ

The energy use for water provision was also explored geospatially. The Energy Intensity of each WRZ was calculated to view the geographical distribution of energy use. Figure 3-3 (a-b) show the contribution from each WRZ to the total energy consumption of the system by WRZ, and the water flow in the same corresponding period by WRZ as well. The figure shows the London WRZ in blue as the largest consumer of both water and energy, due to its size. It is followed by the Swindon & Oxford (SWOX) WRZ both in terms of water and energy use, and then followed respectively by Kennet, Slough Wycombe and Aylesbury (SWA), Guildford and Henley. The category ‘unassigned data’ includes water transferred from water treatment works outside the Thames Water WRZs and energy not allocated to the WRZs. The elements that make up this category in energy and water are different, and could be explored further by the organisation to draw a clearer picture of where water and energy lie in their geospatial territory.

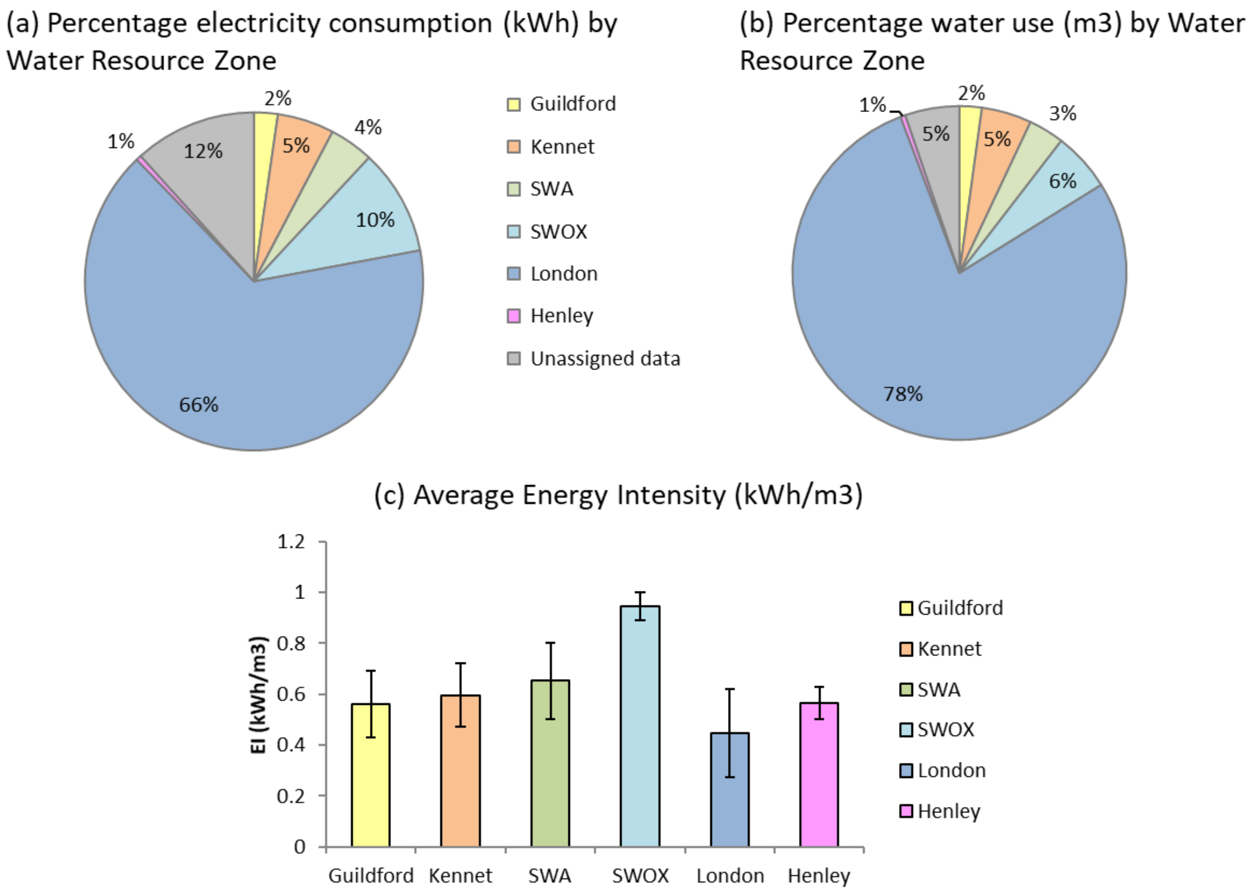

Figure 3-3: (a) Percentage energy use of system by WRZ; (b) Percentage water flow of system by WRZ; (c) Average Energy Intensity of the system by WRZ

Figure 3-3(c) shows the energy intensity of each of the regions, including the standard error for each. It is notable that even if London is the largest consumer of energy, it is the most efficient at delivering each unit of water, although it has the largest standard error in energy intensity due to the large number of sites with different sizes. Conversely, smaller WRZs like SWOX or SWA are significantly more energy intense than London, but have smaller standard errors because there are fewer works, most likely of similar size. London benefits from the Ring Main, a clean water conveying system where flow occurs mostly by gravity from the service reservoirs at the source water treatment works (Smith 2001), which may contribute to the significantly lower energy intensity in the region. London also has some of the largest water and wastewater treatment works in the country, which may benefit from economies of scale when treating larger amounts of water than other smaller regions covered by Thames. Other regions, such as SWOX, have high energy consumption water treatment plants, require more pumping and may have different water quality, leading to more intense treatment of each unit of water. This information could potentially be useful to utilities when targeting energy efficiency in different regions, as differences in geospatial and infrastructure configurations may result in significant variances in energy intensity, and allow for locally relevant solutions.

3.4 Discussion

There have been no published research studies to date that estimate the energy intensity for the water industry in the UK by functional component of the water cycle. Napoli & Garcia-Tellez (2016) highlighted the importance of disaggregation to regional levels when addressing water and energy needs, due to the complex relationship that governs how energy is used for water. Similar studies have been carried out for other regions, such as California and Australia, finding regionally relevant energy-water relationships (Spang and Loge 2015; Cook, Hall, and Gregory 2012). Therefore, this studies' regional approach is appropriate, as although water policies are driven by a national framework, the South East of England has some of the largest population growth and already suffers from water scarcity.

An important contribution of this paper is the provision of Energy Intensities for each functional component of the water use cycle in the UK. This is especially relevant for the UK context because these intensities represent observed ranges of energy used to treat a unit of water across a large sample of asset types and asset combinations. These intensities can be used to support the modelling of different water use cycle energy implications.

The relative efficiencies for treatment of water and wastewater identified in this study were higher than previously reported aggregated figures for the UK. This may be due to continued efficiency increases since 2005/06 in treatment technologies, due to differences between averaging organizations versus measuring a single entity, or due to regional specificities; increases in the quality of data collection and reporting, such as increased metering throughout the Thames system, may also be partly responsible for more accurate figures. The system average energy intensity (approximately 0.89 kwh/m^3) is still however higher than many other similarly industrialized nations such as the Netherlands, or Australia (Kenway et al. 2008; Olsson 2012). This highlights the importance of continuously revisiting energy consumption of such systems to understand changes. Understanding where the hot spots of energy intensity lie can help water utilities target limited resources to the most beneficial areas; for example, by investing in a particularly energy intensive technology in water treatment, or by using renewable energy where the energy consumption cannot be feasibly reduced, as is already happening in the Thames area. Furthermore, working on improving existing infrastructure, and understanding current energy patterns can help in making aging systems perform better.

Figure 3-4 shows the energy intensity of each functional component in the case study (Our Study) compared to the previously reported Water UK Reports figures (Water UK), which are highly aggregated and do not provide information on distribution or the waste networks (Water UK 2006-12). The energy intensity of the functional components shows the range from the lowest energy intensity in the system to the highest, and thus the averages discussed previously are found within these ranges. The upper and lower limits of the boxes in the Figure represent the highest and lowest value in the sample data set for each functional component.

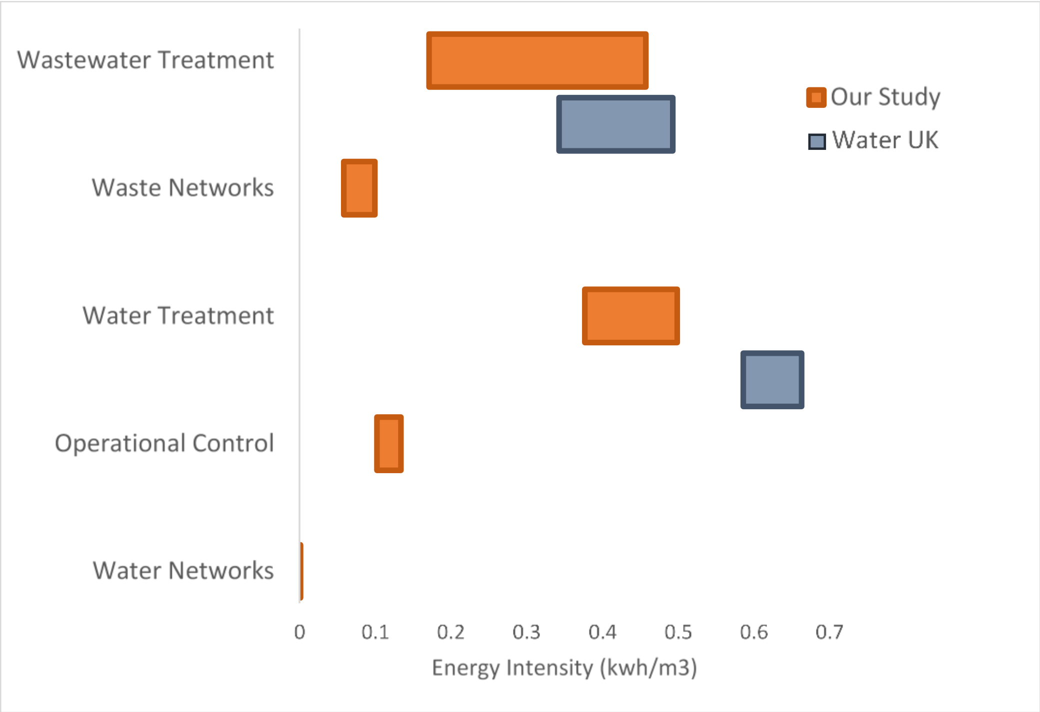

Figure 3-4: Comparison of Energy Intensity against previously reported figures

The range that can be seen for the reported Water UK figures represents the UK total energy used to treat each unit of water and wastewater for the years it was reported in the Water UK reports (2002-2007). These figures were reported as aggregate UK figures in the reports, and noted as sourced from water companies. There have been no other public reports of the energy intensity of the UK water sector from this, or primary sources, since then.

The current study benefited from a large amount of primary data. However, although large amounts of data are generated within the utilities themselves for the purposes of running their businesses effectively, much of this is usually not available for academic purposes. Thus, the body of data available for such studies today is not sufficient to produce a reliable estimate of the true magnitude of the UK's water-related energy consumption. The same can be observed in many regions of the world. As additional and better-quality data becomes available, as a consequence, for example, of metering to comply with the Carbon Reduction Commitment, academics can work with the sector to improve the way data can be used to collaborate.

This study finds that even within a sub-national, regional context, there are differences in the geospatial energy intensity of water infrastructure systems. There are no studies that have looked at geospatial energy use of water infrastructure in the UK, yet this is an area which could provide significant joint water and energy savings, where it is financially viable. In regions such as California, decision-makers are starting to use geospatial energy intensity information to target groups for water saving programs, and reap associated energy savings (Spang and Loge 2015). In the current study, specific regions, for example Oxford, have been found to be more energy intensive than other similar locations in the study area, due to high energy-consuming infrastructure. This may be due to some treatment works in the Oxford area requiring more high-lift pumping than other regions due to the geographical distribution of the works and population, as well as suffering from changing in water quality, such as higher recurrence of algal blooms (Thames Water operations expert, personal communication, 15th July 2015). There is also a lack of space to significantly expand treatment works, which means improvements have been limited. Further enquiry into the reasons for such differences could provide useful guidance for future water planners. Differences in energy intensity across regions can help inform decision-making in water utilities, for example, by using the information to target efforts for water saving campaigns, avoiding particular configurations or allowing space for growth and addition of more treatment in the future. If an area is more energy intense and is mostly domestic, or agricultural, then a water utility may develop a programme to work with end users there to reduce their water use, leading to coupled water and energy reductions. Our results show that even if London delivers the most water, it is the most efficient region in energy use per unit of water. This may be due to the London Ring Main, which uses gravity to move water, contributing to overall system energy efficiency. Thus, targeting energy efficiency in other regions may result in larger proportional gains.

According to Marsh (2008) strategies to reduce energy consumption in the water sector should focus on where and how the energy is being consumed. For example, a large proportion comes from water pumping, so strategies that focus on the reduction of leakage as well as demand reduction could have the most impact. In highly urbanized areas such as London, this is a difficult task as it is costly, and in many cases not viable to reach water pipes. Thus, other strategies, such as more energy efficient pumps to optimise performance can further reduce electricity consumption. The Global Water Research Coalition (GWRC) and the UKWIR (2011) found that pumping is the main energy-demanding operation in water supply and treatment with more than 80% of the total consumption. In our case study, just pumping for operational control for water supply (pumping through the pressurized system) consumes approximately 13% of the total system energy, but this does not consider water abstraction pumping and pumping within the treatment works, reflecting the large cost associated with pumping. There are many ways to reduce the energy and costs of water transport and conveyance; for example, through optimizing pumping in response to energy demand from other areas of the economy, effectively using pumping as a demand response. According to Yang and Yamazaki (2013) installing variable speed drives (VSD) in older pumps can substantially improve pump performance by 5 to 50%, particularly when functioning at lower loads, as pumps are more efficient closer to full load (Cohen, Nelson, and Wolff 2004). It is also important to perform required repairs and maintenance, since aging electric motors are responsible for important phase shifts (when current and voltage are no longer in phase), which causes problems on the grid, as well as inefficiencies. In the Thames Water Annual Report (Thames Water 2016a) reports that to specifically reduce their energy consumption they are planning to continue to upgrade, replace and optimise pumps. Quantifying the specific efficiency gains from these activities could be an extremely useful way to understand the most cost-effective ways to reduce energy consumption in pumping, and could be beneficial to other regions that are just starting to carry out such activities. Water needs to be pumped regardless, and thus, using renewable sources to power pumps in distribution systems can also contribute to reducing electricity consumption from the grid in the sector. Micro-hydro, as well as heat reclamation, are technologies that are being researched and implemented in this area.

It is clear from the results that the energy profile of the treatment of water and wastewater differ significantly in their seasonal patterns of energy consumption.

Further analysis is required to ascertain explanations for variance. The aspect of energy use in water and wastewater treatment has had most of the regulatory and policy attention in the past. It is also still a source of potentially significant energy efficiency developments, and as such should be given the necessary attention and innovation promotion. Any analysis into the future of the energy implications of water and wastewater treatment however, will need to take existing infrastructure, seasonal and treatment differences into account, while considering best available technologies, carbon, affordability to customers, and cost. More studies are now focusing on the framework of energy used in water and wastewater treatment and within the wider system, instead of on specific process technologies, but this is still significant space to understand these patterns better, particularly including geospatial elements, in future research.

The current study illustrates the effect that expansions to wastewater treatment works to meet the European Union Urban Waste Water Treatment Directive (91/271/EEC) and changing environmental conditions has had on their energy consumption. The capacity and treatment increases will reduce the need to discharge untreated wastewater from combined sewer flows and the treatment works to the Thames Tideway (Defra 2012b). The resultant doubling of the energy consumption in the water utility as a whole, even when energy has been taken into account, highlights the impact of water infrastructure investment decisions on energy, and reinforces the importance of assessing infrastructure from an energy perspective (D. Marsh and Sharma 2008).

Towards the future, considering how much additional energy will be needed to treat water to higher standards, as well as to remove additional chemicals (such as pharmaceuticals) requires attention, especially as with current available technologies energy and capital costs will likely be very high. Further research and development is needed in this area to lower the energy intensity of water and wastewater treatment, considering future water quality. On the other hand, if we can avoid watershed contamination then this would reduce the amount of energy needed. Evaluating how watershed protection and ecosystem management can be promoted in key areas to reduce pollution to watersheds that would help to avoid additional treatment investment is equally important. Catchment management is likely to become an increasingly viable option going forward; however, its benefits may take longer to result.

3.5 Conclusions

This study analysed the system in a disaggregated manner and examined the resulting components from different perspectives. The system wide energy consumption of water and wastewater infrastructure systems is not well understood and there are multiple parameters influencing them. These energy patterns are important to understand, to ascertain where we might reduce consumption and make the system more efficient.

This study has identified several energy consumption hot spots related to water and wastewater treatment and transport by using a disaggregated methodological approach. The energy patterns of each section of the water use cycle were studied individually as well as together to identify differences in seasonal patterns, absolute energy values, geospatial differences and energy intensity. Further study into local factors affecting in-system differences could provide additional depth. These might include variations in topography, such as height differences leading to differences in pumping costs, water quality and geology, which can influence the amount of chemical loading required in a treatment work, or rural versus urban populations and land use, which can influence runoff and water quality in works. This study could be used as the basis for future assessments that consider the energy use of water systems and considered as part of studies that evaluate different options such as catchment management versus technology, versus centralization and other strategies.

Clean water treatment is shown to be the more energy intensive component of the cycle, which reinforces the need to continue to research and invest in technological innovation in clean water treatment, alongside wastewater treatment. It also offers an opportunity to further investigate alternatives in relation to the management of works, regulatory options and how catchment management may contribute to reducing some of the energy consumption. A further contribution of this study is the finding that even within a sub-national, regional context, there are differences in the geospatial energy intensity of water infrastructure systems. Specific regions have been found to be more energy intensive than other apparently similar locations in the study area, due to high energy-consuming infrastructure. Such findings yield areas of energy intensive water infrastructure, and patterns of consumption that could help in the integrated management of water and energy interdependencies.

4. Multi-objective Robust Decision Making for integrating energy use in water resources planning

4.1 Introduction

Water resource planning is widely regarded as a problem of decision making under uncertainty. The planning problem is conventionally framed as one of selecting 'least-cost' options to achieve the desired security of supply. However, whilst energy costs are one of the greatest operational costs of water utilities, the changing nature of energy use in water resource systems has not been quantified on a sound empirical basis in past calculations. A Water-Energy Model that incorporates energy costs of running a water supply system is demonstrated using a UK water utility. Multi-objective optimization is used to evaluate trade-offs between water supply plans using three main performance metrics: security of supply, capital investment costs and operational energy expenditure. The study uses Robust Decision Making to explore the implications of uncertainty for alternative plans. The study finds that without the consideration of operational energy costs, other plans would have emerged as more attractive, but would have had significantly higher costs in the long-term. The study also shows that demand management focused on reducing per capita demand could reduce the vulnerabilities of long-term plans, both in security of supply and in energy costs.

4.2 Methods

This section introduces the case study location and details, the simulation framework presenting the water resource system model, including the performance metrics used and how energy is incorporated. A list of identified uncertainties is presented in the context of RDM and its application to the case study. The multi-objective optimization is described including its application to RDM.

4.2.1 Case study

The Thames region, served by Thames Water Utilities Ltd., in the South East of England, is used as an illustrative case study. The Thames region has a per capita water demand of 160 litres per person per day on average and serves between 10-12 million customers. It is also one of the most water scarce regions in Europe due to the high demand from population and industry, relative to the average rainfall of 690 mm/year over the 16,000 km^2 catchment (British Geological Survey (BGS) 2017). The Water Exploitation Index (WEI) for the region, which represents the mean annual total abstractions of water in a region divided by the amount of resources available to it, identifies the South East of England to be as water stressed as countries like Spain and Italy (Kowalski et al. 2011). Pressures on water supplies are set to intensify in future with increasing population size and environmental regulation. The impacts of climate change on precipitation and evapotranspiration will further compound this and is also a major source of uncertainty.

4.2.2 Simulation model

4.2.2.1 Model overview

A water-energy interdependencies model, known as the Water-Energy model, has been developed for this study using empirical data provided by the water utility. This data is used to simulate a water supply infrastructure system with associated energy costs. In this study, ‘energy’ represents electricity consumption. Thus, the simulation model focuses on the net electricity imported into the system and uses this as the operation cost reduction objective. This objective is based on the utility's objective to reduce water supply net grid electricity import, and as the main cost in operational expenditure.

The purpose of the model is to help understand how the energy costs of water supply systems may change in the future and how this may help inform decisions about future water supply options. The indicative energy costs for each stage of the water supply system are calculated for a number of future scenarios, and tested within an RDM framework. These stages include water withdrawal, water treatment and water distribution. A water demand module was also built which calculates a monthly water demand. The total energy costs are then calculated for each of the stages using the parameters and formulae described in the following sections. An overview diagram can be seen in Figure 4-1, each module is explained in detail in the subsequent sections.

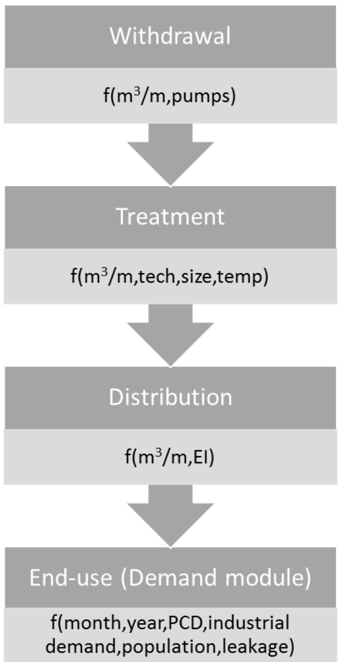

Figure 4-1: Overview of Water-Energy model

The main input to the model is the fresh water flowing through the infrastructure in m^3 per day (Water Available for Use – WAFU), as well as the calculated energy intensity of each stage, which is aggregated to total kWh per month (as is done by water utilities). The model also calculates total water demand by combining per capita demand (pcd) and population. The simulation runs start in 2010, where it is based on approximately 5 years of empirical data, which are replicated. Then, a 20-year simulation (2015-2035) provides a projection of water demand, supply and associated energy costs. The simulation is run under a set of uncertainty parameters described in detail in section 4.2.4.

4.2.2.2 Water demand & supply

The model is characterized by a water demand module that drives how much water is needed by the system. This function is made up of the Thames Region domestic population (household demand) with a starting water demand of 160 l/p/d, and an average 1,450 ML/d, as well as a constant industrial demand (which includes commercial) of 480 ML/d (Thames Water 2014b). The demand stage also has a starting population of approximately 9.04 million that corresponds to Thames Waters' WRMP (Thames Water 2014b). The household demand and population growth are treated as uncertain and described in detail in section 4.2.4. The leakage in the system is also calculated at this stage. In other iterations of this study, the leakage could be treated as uncertain depending on different leakage reduction strategies. In this study, it is included to better represent the water needed in the system, but not treated as uncertain. Empirical leakage figures are used for the first 57 months, with an average of 650 ML/d. The average monthly mean and standard deviation are then calculated from the empirical dataset and used to generate monthly projections for leakage until 2035.

The water demand stage is thus a function of per capita demand, industrial demand and population growth. The equations to calculate demand are:

$$PCD_T = PCD_B + (PCD_B * C_{PCD}) \tag{1}$$

where, PCD_T is the total per capita demand for a certain month and scenario, PCD_B is the per capita demand for that month and C_{PCD} is the variation in per capita demand corresponding to each of the three scenarios described in the uncertainty section (which can be positive or negative depending on the scenario). Similarly, with population growth:

$$PP_T = PP_B + (PP_B * C_{PP}) \tag{2}$$

where, PP_T is the total population for a certain month and scenario, PP_B is the population for a specific month, and C_{PP} is the change in population for that specific month and scenario in the uncertainty section. The final water demand for the model is:

$$W_D = (PCD_T * PP_T + IND + L) \tag{3}$$

where W_D is the total water demand for the system in meters cubed per month, IND is the industrial demand and L is the leakage for that month. IND is assumed to remain constant, in line with Thames Water's WRMP projections for the region (Thames Water 2014b). W_D is used as the water demand to be met by the infrastructure system in the subsequent steps of the simulation framework.

The water supply is also defined in this stage as the amount of water available for the utility to extract using its existing water infrastructure system. 57 months of empirical data are available to calibrate the model. The projections for water supply are obtained from the Thames Water WRMP (Thames Water 2014b). Any new infrastructure options provide 'new' water that can be added to the water available for supply. Thus, the current the model has a requirement:

$$W_s + W_{IP} = W_D \quad (4)$$

where, the water available for supply (W_s), up to the capacity of the existing infrastructure system, plus water provided by any new infrastructure options (W_{IP}) needs to equal water demand. The model makes certain assumptions, such as that all proposed infrastructure options provide new water, which could be modified in more detailed models to include already existing water as 'recycled' water.

4.2.2.3 Water withdrawal

The withdrawal stage is characterized by groundwater abstraction points, and surface water abstraction points. The study base scenarios use the existing Thames Water system abstraction proportions of approximately 80% surface and 20% groundwater. A pump efficiency of 75% is assumed throughout the model (Ofwat 2010a). These parameters can be varied in the model to visualize the difference that pump efficiency makes on energy consumption, versus the depth of a well, etc. The energy consumption from the pumping at this stage is calculated using the following equation from Cooley and Wilkinson (2012), who apply it to calculate the energy costs of water source extraction:

$$E_a = (W_S gh)/e \quad (5)$$

where, E_a is the energy consumption in Joules (then converted to kWh), W_S is the water being abstracted (which is transformed from m^3 into kilograms), g is the gravitational constant of 9.81 m/s^2, h is the depth the water is lifted by in meters depending on the water source type, and e is the pump efficiency (with no units), set at 0.75. The water withdrawn moves to the water treatment stage from the withdrawal stage.

4.2.2.4 Water Treatment

The water treatment stage is characterized by a set of treatment works with specific technological make-ups. The model has the flexibility to build different plants with specific technologies. The contribution to the energy intensity of additional treatment works technologies was obtained from the literature (Electric Power Research Institute 2013). This is because the empirical data available for this stage was only at the whole treatment work level and not by technology. It is possible, for example, to choose a conventional treatment works, made up of source water pumping, rapid mixing, flocculation, sedimentation, chemical feed systems, backwash water pumps, residuals pumping, thickened solids pumping, finished water pumping, and non-process loads. However, there are several technologies in the model, which gives it the potential capability to build treatment works with different make-ups, as well as with different capacities (see appendix section 9.1). For this study, the treatment stage is comprised of all the major processes in current treatment works in the Thames Water Region and their corresponding energy intensity. A regression equation from the empirical data is used to calculate the energy consumption of the treatment works (see appendix section 9.2). The total energy use of the treatment stage is a function of the treatment work capacity and flow, and the temperature in each month:

$$E_T = (-0.0013T+0.45)*W_S \quad (6)$$

where E_T is the energy use of treatment in kWh/month, T is the regional temperature and W_s is the water flow for a particular month and scenario in m^3/month. The equation was derived from empirical data analysis, so there could be further influencing factors not captured by the equation and its applicability to other studies is limited.

4.2.2.5 Water distribution

The distribution stage represents a high-pressure distribution system. As there was empirical data available for the Energy Intensity of this stage (0.118 kWh/m^3), this value was used to represent the energy consumed at this stage. Thus, the equation that represents the water distribution stage is as follows:

$$E_d = EI_d*W_S \quad (7)$$

where, E_d is the total energy required for the water distribution stage, EI_d is the energy intensity of the stage and W_S is the water supply for that month and that particular scenario.

4.2.2.6 Total energy consumption

The total monthly energy used in the subsequent steps of this study is calculated by adding the total energy consumption at each stage of the water supply system described above, as follows:

$$E_T = E_a + E_t + E_d \quad (8)$$

where, E_T is the total monthly energy consumption in kWh, and E_a, E_t and E_d are the energy consumed in the abstraction, treatment and distribution stages respectively. E_T is converted to £ by multiplying each monthly energy consumption value by the energy price (£/kWh) and discounted at 3.5% for the number of years in the simulation. The discount rate is set at 3.5% in line with the industry average, and the WRMP projections (Thames Water 2014b). Chapter 6 carries out an analysis of how changes in discount rates affect changes in costs. The energy price forecasts to 2035 are obtained from the UK energy and emissions forecasts for 2015 and are not treated as uncertain (DECC 2015a). In other iterations of the model the energy price could be varied to evaluate the impact of energy price on water supply decisions based on energy costs.

4.2.2.7 Model calibration

The model is calibrated to ensure that the output is consistent with the historic empirical data provided by the utility and with the assumptions used by Thames Water in their Water Resources Management Plan with current electricity consumption. To do this, the model output is validated with 5 years of available empirical energy consumption. Figure 4-2 shows a time series of the empirical energy consumption for water supply and the simulated energy consumption data. The model captures peaks in the data well, but does not do as well with the troughs.

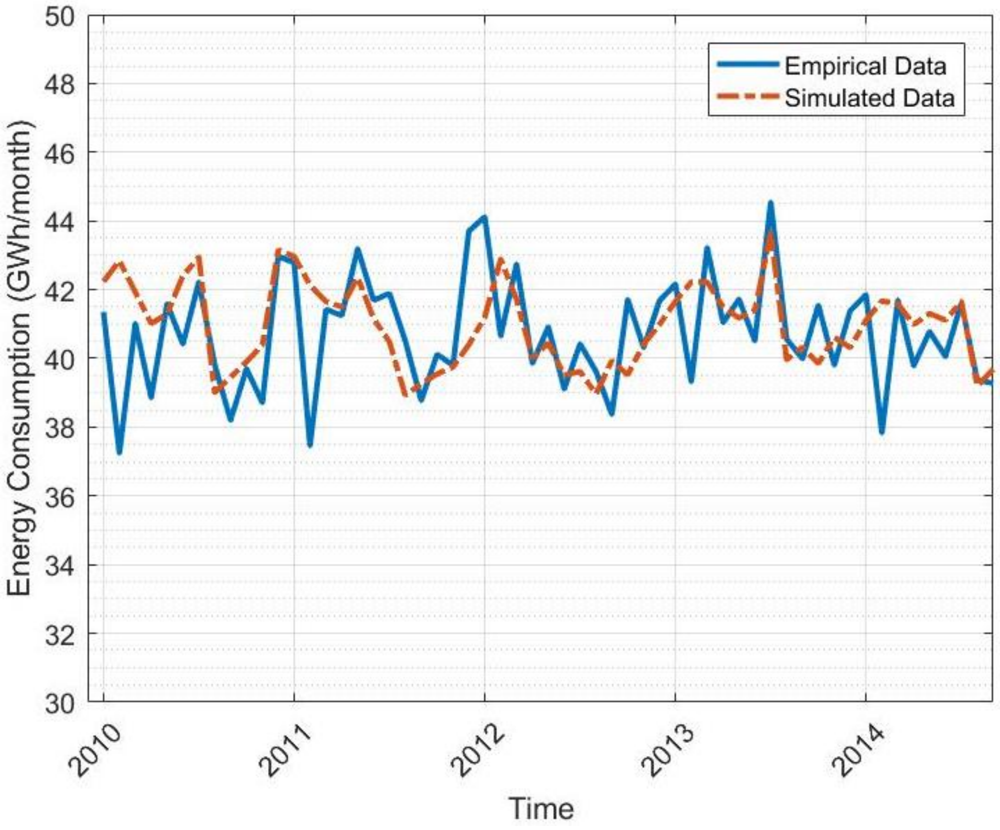

Figure 4-2: Empirical energy consumption of water supply over 5-year sample period compared with simulated energy consumption of water supply from model (GWh/month)

4.2.3 Supply and demand options

The study focuses on two main aspects of the water resources management: proposed supply options and drought management options. First, proposed infrastructure options from the current Thames Water Resources Management Plan are evaluated (Thames Water 2014b). These options are selected from the WRMP options considered, and include a range of different types of supply to capture all the types of water supply options available to Thames (Table 4-1). The operational energy use is calculated for each option and added to the baseline energy cost E_T described above. The planned options operational costs are also multiplied by the energy price forecast and discounted to 3.5% per year. Thus, the decision variable becomes:

$$E_n = (E_T + E_{IPs}) \tag{9}$$

where E_n is the total discounted operational energy consumption of the system in kWh including the operational costs of additional infrastructure options or portfolios (E_{IPS}). The objective is to evaluate which option or groups of options can meet demand at the lowest operational energy and capital investment cost. Thus, the model calculates the ability of the established water infrastructure system plus any additional options to meet water demand (W_D). The model assumes that new options only need to be delivered when the water available for use is lower than water demand, and they are used up to the difference between water demand and water available for use, as described above. The proposed infrastructure options all have associated capital expenditure costs, which can be seen in Table 4-1 and were obtained from the Thames Water WRMP.

Second, the measures that Thames Water uses to produce extra supply during a drought are included in the model, to represent available water supplies more accurately. They are the main strategic schemes used to avoid service interruption in the future (Thames Water 2013), and are only used during drought periods. This study looks at the operational costs of each of these 'drought relief' supplies (which are already built – so have no additional capital expenditure to quantify) to aid decision-makers to use energy efficiency as a decision tool.

The drought options have a limit on the amount of times they can be used over a given 24-month period. In the current iteration of the model, they can only be used for up to 10 months in a row during a 24-month period (Thames Water 2014a). The options are used when water available for supply is lower than demand in a specific month. The 10-month limit is set because it was an average time-period that could be applied to all drought management options. Some could be used for longer or shorter periods depending on the type and location, but the average time is 10 months, so this was chosen as a middle benchmark, which could be modified in further iterations of the model. If demand is still larger than supply, including drought options, then the 'proposed options' come in. The model records each month in which they have been used and if they are used more than 10 times in a row over a 24-month period they are not used again until the next 24-month period.

There is a total of 20 options that are considered to build infrastructure plans, including 8 drought management options and 12 ‘strategic options’. There is also a Business as Usual (BAU) scenario, which assumes no change in the current management or any changes or additions to the infrastructure of the system, which represents a baseline. The ‘strategic options’ to meet water demand and reduce energy consumption in the system are organized into six categories: ‘raw water abstractions’, ‘bulk water transfers’, ‘effluent reuse’, ‘new reservoirs’, ‘desalination and ‘demand reduction’ (Table 4-1). The options described in the table refer to specific options considered by Thames Water, however, the specific details of each scheme are not directly relevant to this assessment. Even though it is useful to assess the operational costs of individual Infrastructure Options, these cannot meet demand alone. Thus, the model analyses them as part of ‘plans’ that are designed to fully meet demand in the model and provide a robust solution.

Table 4-1. Infrastructure Options used in the model, including the type of options, start date, yield, CAPEX and Energy Cost

Variable Code	Category	Type of option	Earliest potential start date (Year)	Estimated yield (Ml/day)	CAPEX NPV (£000)	Energy Cost (kwh/m^3)
Hodd	Raw water imports into basin	Drought Relief	2015	19	-	0.07[a]
Berk	Groundwater Supply	Drought Relief	2015	66	-	0.15[b]
desal50	Desalination	Drought Relief	2015	150	-	2.45[c]
desal150	Desalination	Drought Relief	2015	50	-	2.45[c]
ELRED	Groundwater Supply	Drought Relief	2015	28	-	0.084 [d]
CHARS	Aquifer Recharge	Drought Relief	2015	12	-	0.084[d]
NLARS65	Aquifer Recharge	Drought Relief	2015	130	-	0.23[e]
NLARS130	Aquifer Recharge	Drought Relief	2015	65	-	0.23 [e]
SLARS	Aquifer Recharge	Raw water abstraction	2019	19	89,397	0.23[f]
Canal	Raw water imports	Bulk water transfer	2021	17	59,008	0.13 [g]
RWT75	Raw water imports	Bulk water transfer	2021	75	289,941	0.14 [h]
IPR50	Effluent Reuse	Effluent Reuse	2020	50	162,400	0.74 [i]
IPR150	Effluent Reuse	Effluent Reuse	2020	150	260,573	0.74 [i]
RES50	Water storage	New reservoir	2026	50	745,284	0.33 [i]
RES150	Water storage	New reservoir	2026	150	1,212,874	0.33 [j]
desalsouth50	Desalination	Desalination	2018	50	390,864	2.4 [k]
desalsouth150	Desalination	Desalination	2018	150	580,885	2.4 [k]
DMM1	Demand management	Demand reduction	2015	232.16	526,304	-
DMM2	Demand management	Demand reduction	2015	185.98	520,301	-
DMM3	Demand management	Demand reduction	2015	187.37	480,202	-

Table 2 notes:

a assumes a pipeline length of 19km and that no further treatment of the water is required

b assumes average depth of 40m, and no further treatment needed.

c from TW documents

d assumes 20m depth, and no further treatment needed.

e assumes same value as SLARS

k assumes same as Beckton, slightly more efficient as new build.

f from Matrosov et al (2013)

g assumes length of 20km, pumping intensity of 0.12 (from empirical Thames data and 0.0005kWh/m3/km (Plappally & Lienhard V 2012)

h assumes length of 40km, & pumping intensity as in *g*

i assumes average residential wastewater reuse value from Plappally & Lienhard V (2012)

j average pumping costs for Thames empirical data (minus any treatment costs)

4.2.4 Uncertainties

The uncertainties considered in the study are changes in household demand, changes in population, and climate change effects, up to a 2035 planning horizon. As described above, the Water-Energy model runs until 2035, with empirical data from 2010-2014 and projected data for 2015-2035. There are other uncertainties not considered in the study, including aging of infrastructure, change in industrial water demand, discount rates, other intrinsic model assumption uncertainties, and changing socio-economic factors.

4.2.4.1 Population growth

The parameters are all based on those found in the Thames Water Region. The starting population is 9,043,000 (Thames Water, 2014), as this is the measured population by the Thames Water Resources Management Plan (WRMP) at the start of the period. There are three population growth scenarios based on the Thames Water WRMP population projections for the region. The middle scenario replicates the main population projection by TW, and the low and high represent the lower and upper bounds of this projection. The projected population in 2035 has lower and upper bounds of 10.75 to 11.75 million, which the model replicates.

4.2.4.2 Per capita water demand

There are three demand scenarios used. In the WRMP the per capita daily demand in 2010 was set at an average of 160l/p/d (Thames Water 2014b) which was the starting point for the Water-Energy model. The model then projects a constant demand, a modest increase in per capita demand (165 l/p/d by 2035) and a reduction in per capita demand (150 l/p/d by 2035), in line with the WRMP demand projections for the region to 2035 (Thames Water 2014b).

4.2.4.3 Climate change

Climate change impacts are represented through the Water Available for Use (WAFU) figures. The WAFU projection figures are taken from the Thames Water WRMP (Thames Water 2014b). These figures represent the water company's projection on how much water will be available for delivery to customers. The projections have upper and lower uncertainty bounds of approximately 100ML/d by 2035. In order to represent this uncertainty, precipitation forecasts for 2035 derived from the UKCP09 weather generator are used as a proxy to generate scenarios within the uncertainty space. 100 random sample runs of the medium emission weather generator (a1b) scenarios (at 1.5m) are randomly chosen from the over 1000 model runs to represent several possible projections of the 2010-2039 time slices (UKCP09, 2015). The percentage changes are normalised to the upper and lower uncertainty bounds of the TW WAFU projections to thus represent a distribution of water available to use. These runs are extracted for each month of the year, as the model runs on a monthly time-step. The climate scenarios used are the UKCP09 (2015) regional climate projections; specifically, the projections of mean air temperature (in °C) and precipitation (in mm) over the Thames Basin. The probabilistic climate predictions are based on the family of the Met Office Hadley Centre climate models (HadCM3), which are the most recent downscaled climate scenarios for the UK (Met Office 2016).

This is a simplified approach to considering climate change uncertainty; particularly taking into account that evapotranspiration is also an important factor in determining water availability, that was not considered in this model. However, the objective of these calculations was to represent water availability uncertainty and variation in the range of scenarios and not to develop a detailed hydrological model. The model has the flexibility and potential to be coupled with a detailed hydrological module in the future to more realistically describe changes in the water availability in the Thames Basin.

4.2.5 Multi-Objective Robust Decision Making

The RDM methodology requires performance metrics to classify each model run. Three performance metrics are established to measure the trade-offs between the infrastructure options. Because the objective of this research is to evaluate how energy costs can support the decision-making process for water supply, the performance metrics are: (1) to minimise discounted operational energy costs (E_{new}), (2) to minimise net-present value (NPV) of capital investment costs and (3) to maximise the security supply of the system.

Multi-objective optimization is used to evaluate the trade-offs between the three objectives for sets of infrastructure plans. The optimization is carried out using a multi-objective evolutionary algorithm evaluates trade-offs between multiple objectives and builds a 'Pareto approximate set', which is the best-known approximation to the Pareto optimal set (Kasprzyk et al. 2013). An ε-dominance multi-objective evolutionary algorithm (εMOEA) was used, as this algorithm has been successfully applied to solve water resources problems (Borgomeo et al. 2016; Mohammad Mortazavi-Naeini, Kuczera, and Cui 2014; Mohammad Mortazavi-Naeini et al. 2015; Mortazavi, Kuczera, and Cui 2012).εMOEA use the ε-dominance concept to divide the objective space into hyperboxes of size ε and allows only one nondominated solution to reside in each box (Laumanns et al. 2002). Inclusion of this concept in an evolutionary algorithm produces a method capable of maintaining a diverse and well-distributed set of solutions with a small algorithmic computational cost (Deb, Mohan, and Mishra 2003).

Based on previous applications of εMOEA to water resources optimization studies (Mohammad Mortazavi-Naeini, Kuczera, and Cui 2014; Mohammad Mortazavi-Naeini et al. 2015; Mortazavi, Kuczera, and Cui 2012) the following εMOEA parameters were set: (i) probability of crossover =0.95, (ii) probability of mutation = 0.005, and (iii) probability of inversion = 0.001. The maximum number of iterations was set to 4,000. The εMOEA epsilon values were set to 100 for the first two objectives (capital and operational energy costs) and 0.01 for the third objective to be sufficiently small to ensure high resolution. The termination condition was defined as either reaching the maximum number of iterations or no changes in the Pareto frontier for 200 iterations. The multi-objective optimization was performed using a i5 Intel Core machine with a 3.4 GHz processor on a 64-bit operating system. 100 iterations on a single core took about 1.5 hours. To make sure the model converged, the optimisation was run with different seed numbers. The results presented in this paper are the non-dominated solutions of 9 runs. It is common to perform a few runs in evolutionary algorithm studies to ensure that the best optimal solution is achieved (Eusuff and Lansey 2001; Carr 2014). In this case, the Pareto frontiers generated overlap with each other early on, so 9 runs were deemed sufficient. Appendix section 9.3 shows the output of four of the final runs, where it can be seen that they have converged to Pareto frontiers in the same range, with several overlapping data points. The figure in 9.3 shows capital investment along the x axis, operational expenditure on the y axis, and is coloured by Security of Supply, in the same format as Figure 4-5 in section 4.3.1.

Robustness is commonly described in Water Resources Management literature as the degree to which a water supply system performs at a satisfactory level across a broad range of plausible future conditions (Groves et al. 2008). The performance is measured in terms of a 'Security of Supply' metric, which is defined as: the proportion of simulations for which water demand is fully met (Groves, Ramos, and Cabanillas 2015; Kasprzyk et al. 2013), i.e. S/U.

where S = number of scenarios in which supply meets demand at all times and U = total number of scenario combinations (of supply and demand) considered.

The energy consumption criterion is measured based on one of Thames Waters' objective specifically to reduce water supply net grid electricity import. It is measured as the total electricity consumed by the system plus the selected infrastructure options during each simulation run. It is acknowledged that in reality, operational expenditure is made up of more elements than energy costs, as this includes personnel costs, chemical costs, capital maintenance costs and taxes, which could not be reflected due to lack of data and additional complexity. The costs generated by the model thus are not the total operational costs that would be incurred in the long term by a water utility, but are those related to operational electricity consumption. The results and rankings in the model are based on using energy consumption as a surrogate for operational costs.

The third criterion is the capital investment (CAPEX) of each group of options. The indicative cost of each infrastructure option is ranked based on their cost in £000s. Figure 4-3 below shows a schematic of how the Water-Energy model is integrated with the MOEA which creates a set of optimal plans that maximise Security of Supply (SS) and minimize Operational Energy (Op Energy) and Capital Expenditure (CAPEX).

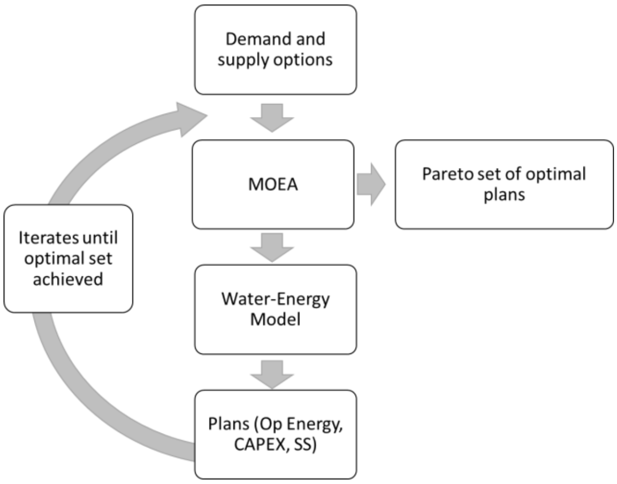

Figure 4-3: Schematic of Water-Energy model and MOEA integration

4.2.5.1 Quantifying robustness

RDM requires a method to quantify robustness as well as a method to analyse uncertainty. A multi-criteria analysis deviation analysis is carried out in which normalised figures of the metrics are added into one criterion, to select the overall best performing strategy in the three performance criteria (Matrosov et al. 2013). In this context, a regret-based metric is used, which quantifies how much of a strategy's (s) performance (P) deviates from the performance for the criteria chosen of the ideal (best-performing) strategy (s') in each performance criteria (c), for the same set of input parameters (future scenarios) (j), as follows:

$$\mathrm{Dc}\ (s, j) = |\mathrm{Pc}\ (s', j) - \mathrm{Pc}\ (s, j)| \quad (10)$$

Deviation is then aggregated (D_a) for each metric's normalised values to result in a measure of deviation of optimality out of 3. Thus, the normalised aggregated measure for each set of future conditions is as follows:

$$D_a(s,j) = \sum_{c=1}^{n} D_c(s,j) \tag{11}$$

where D_c (s, j) is a standardised measure representing the quantified robustness for criteria *c,* and *n* is the total number of performance criteria. As the performance metrics used in this analysis are not comparable numerically, they are normalised to fall within [0, 1] values:

$$D_c(s,j) = \frac{|P_c(s',j) - P_c(s,j)|}{|P_c(s',j) - P_c(s^*,j)|} \tag{12}$$

Where s* = the worst performing strategy for each set of future conditions where the lower the deviation values the closer to the ideal strategy

4.3 Results and Discussion

4.3.1 MORDM results

The robustness of 76 unique combinations of supply infrastructure options was investigated considering uncertainty in exogenous parameters. Each of these unique combinations is numbered from 1-76 and described in Table 4-2. The multi-objective optimization maximised the security of supply of the water supply system for the sets of plans, while minimising capital investment costs and long-term operational energy costs. The table shows how the options were grouped into plans through the optimization exercise, as well as the specific components found in each plan, where they are found on the Pareto frontier within figures 4-4 and 4-5, and the average security of supply provided by the group of plans.

Table 4-2. Options, corresponding plans, group and average security of supply

Options (major components)	**Plans**	**Group in Fig.**	**Av. Security**
Canal	7,10,15,18,22,23,24,27,31,32, 44,45,55,62,64,67,68,71,72	A+B	0.864
Canal + SLARS	16,17,29,33,42,43,46,76	A+C	0.902
Canal+IPR50	1,3,6,26,50	A+F	0.954
IPR50	4,5,52	A+F	0.95
IPR50+SLARS	14,19	A+F	0.955
SLARS	41	A	0.913
RWT	2,8,12,34,35,58,61,73,74,75	D	0.92
Canal + RWT	11,13,25,30,47,54,57,60,66,70	E	0.936
IPR150	56	F	0.987
Canal+IPR150	37	F	0.99
Canal+IPR150+SLARS	36	F	0.994
Canal+IPR50+SLARS	9	F	0.962
Canal+SLARS+RWT	21,28,38,40,48	G	0.954
DMM1	59	H	0.994
DMM2	20,49,63,65	H	0.986
DMM3	53,69	H	0.99
Canal+DMM2	51	H	0.992
Canal+DMM3	39	H	0.994

Figure 4-4 shows the multi-objective optimization trade-off results for the model cases. The figure shows the operational energy consumption on the X axis, capital costs on the Z axis and security of supply on the Y axis for a set of Infrastructure plans. Each numbered circle on the plot represents one of the unique combinations of different infrastructure options. These numbers are coloured by their relative security of supply percentage to facilitate visualization in addition to security of supply also being represented on the Y axis.

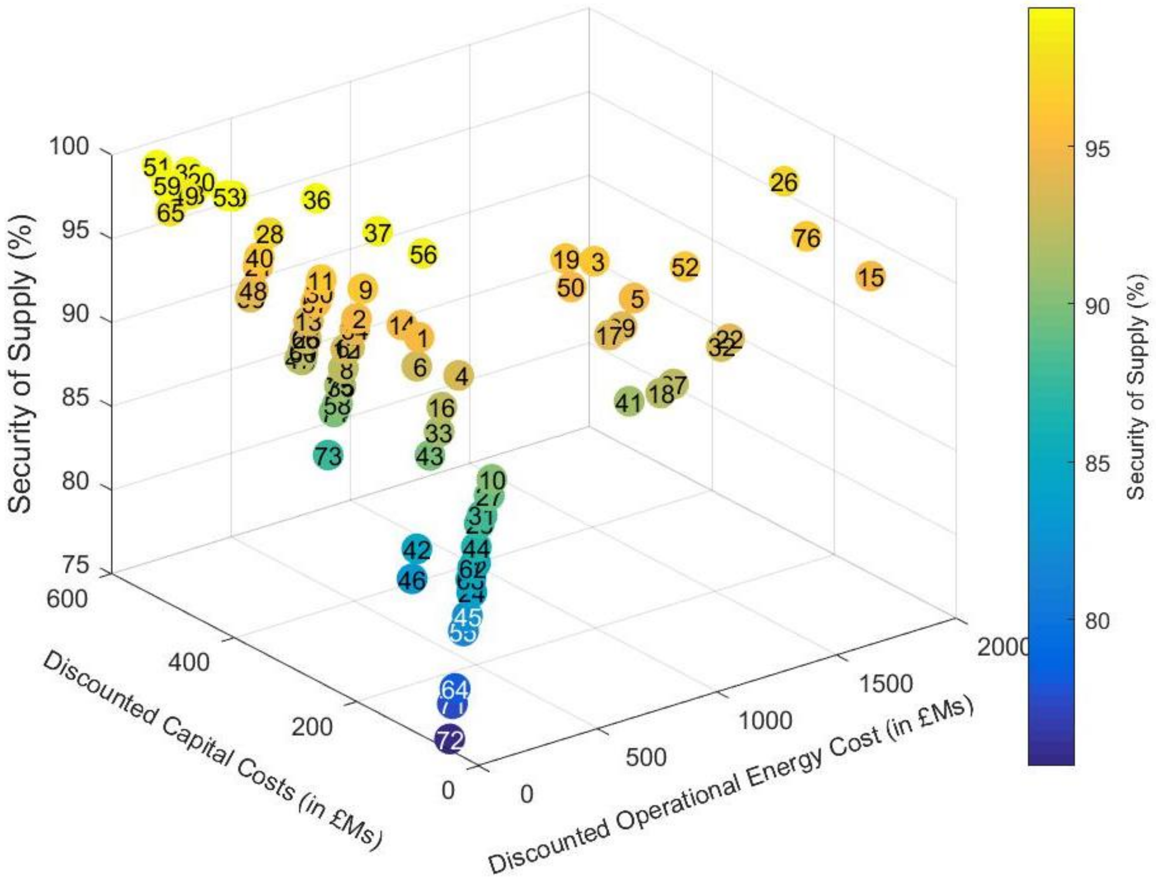

Figure 4-4. Multi-objective optimization trade-off results between the three performance metrics in discounted life costs

Figure 4-4 shows that to provide high security of supply within the water supply system in an uncertain future, some capital and operational costs will be incurred. The results show that higher investment is needed to improve security of supply, although less so with higher operational costs and more so with higher capital investment.

The discounted cumulative cost of grid electricity is larger than the capital expenditure for the options. These may seem very large, but Thames reports to Ofwat show that their annual average operating expenditure for water delivery is £327 million a year (Ofwat 2010b), which cumulatively over a 25-year period would equate to approximately £8.2 billion, though as explained above this includes other costs besides energy. Thus, the trade-offs could be said to be biased because capital investments can incur running costs that have not been included. However, the characterization of the options in this way can be useful in order to visualize how trade-offs occur and to group types of solutions together.

Figure 4-5 shows the trade-offs between the three-performance metrics on two axes, with capital investment on the x axis and operational energy costs on the y axis and the security of supply percentage as a colour on each unique plan. Groups of plans that have similar infrastructure option combinations are shown as groups labelled from A-H. The figure shows there are three types of groups: groups with low capital investment but high operational costs and middle-range security of supply (group A), groups with low capital investment, and low operational costs but low security of supply (groups B, C, D, E) and groups with higher capital investments, lower operational costs but higher security of supply (groups F, G, H). Thus, higher security of supply is obtained either at the expense of higher capital cost, or higher operating cost. Table 4-2 above shows the options that are part of each plan, as well as the group where they are found within Figure 4-5 and the average security of supply for the group.

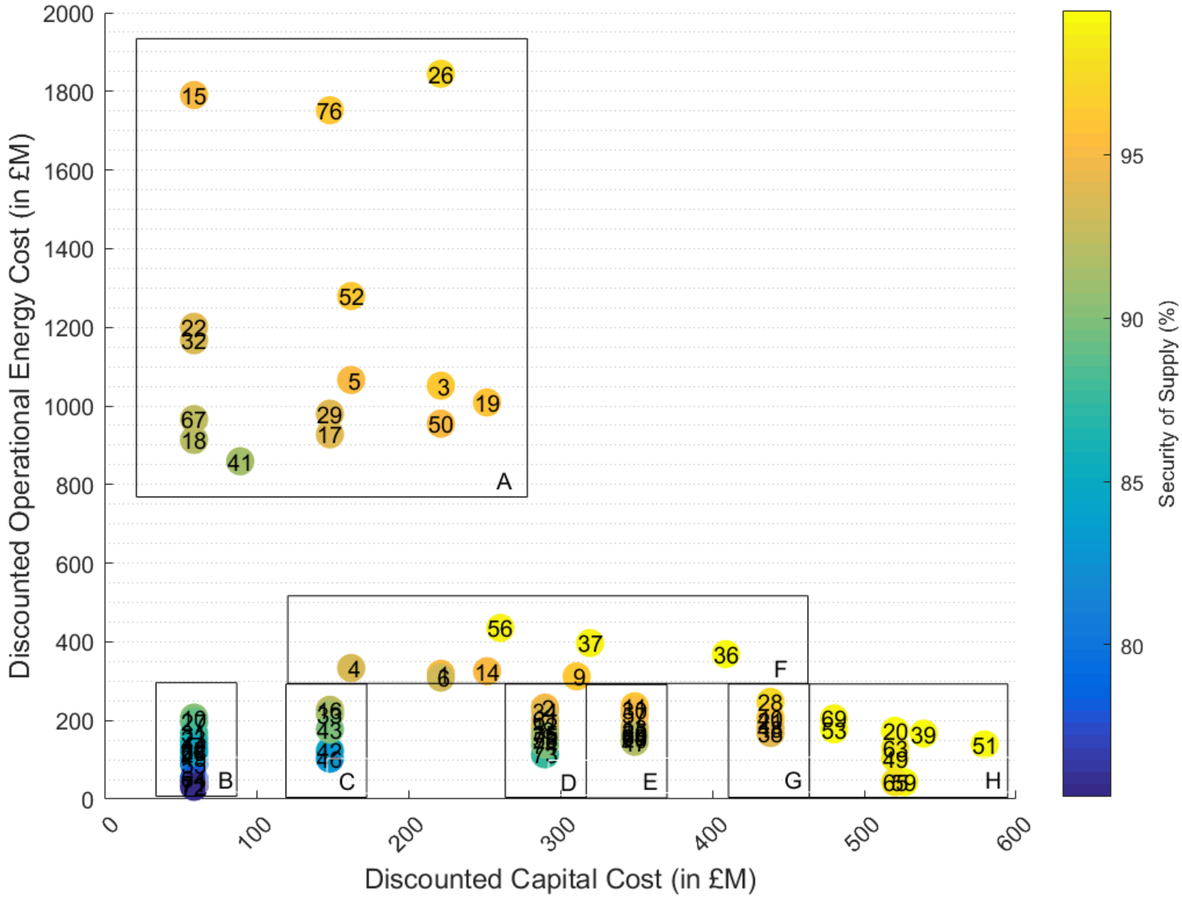

Figure 4-5: Infrastructure plan trade-offs between OPEX and CAPEX in discounted life costs

This figure also shows how security of supply increases with CAPEX, but not so with OPEX. Meaning that higher investment in CAPEX results in improved security of supply, but there is a limit to how much improvement can be made from increasing operating costs. The relationship in Figure 4-4 is shown in 2D in Figure 4-5 to facilitate discussion of the results.

In reference to the plan groupings in Table 4-2, even though the canal component is incorporated into the greatest number of IPs, on average when it is used in isolation with different drought management schemes (group A+B) it provides the lowest security of supply of all groups of IPs at an average of 86.4%. When the canal option is used in combination with other small supply side schemes such as aquifer recharge or indirect potable reuse (groups A, C and F) the average security of supply increases to a range between 90.2% and 95.%. These options already provide relatively high reliabilities.

The highest security of supply is provided by plans within groups F and H, which incur higher capital investments costs but low operational costs, such as plans 36, 39, 51 and 56. These groups are characterised by including larger effluent reuse schemes and demand management options, often grouped with a canal option or other small infrastructure options. The security of supply of the plans like this found in these groups ranges from 99.2% to 99.4%, and they have relatively low operational costs, as compared to other costlier options such as desalination. These strategies would require higher capital investment in the short-term, but would permit significant long-term savings for water utilities.

Therefore, in the context of the model, the best combination of options would almost always include demand management options with some effluent reuse and other smaller schemes.

This solution was compared to the Thames Water 2014 preferred supply and demand plan from the Water Resources Management Plan to check whether they matched the conclusions from their decision-making process. The 2014 preferred plan for the whole Thames Region includes demand management in the short-term, progressively larger groundwater schemes in the medium-term, and the development of a canal and a large wastewater re-use plant in the longer term, towards 2030. The complementarity of these solutions to the results of our Water-Energy model provide legitimacy to the model outputs. In the preferred plan section of the Thames WRMP, a sensitivity analysis of the preferred plan to different futures is also carried out to evaluate the outcomes.

Other noteworthy plans are the group with very low capital costs but high operational costs (group A). These plans include those such as plan 15, plan 76 and plan 26. These rely on a combination of smaller investments that are costlier operationally in the long-term, usually always in combination with the canal. The three plans seen in the top left corner of Group A in Figure 4-5, provide security of supply of over 95%, and low upfront capital investment costs, but do have the highest discounted energy costs in the long-term. When not considering long-term energy implications in detail, portfolios like plan 15 and similar ones could appear attractive, due to high security of supply and low capital investments. However, as can be seen when long-term operational costs are considered, they become significantly more unattractive than other portfolios that may have higher upfront costs but significantly lower lifetime energy costs.

4.3.2 Selecting a candidate strategy

The MORDM sampled many combinations of alternative future conditions in which the trade-offs were tested. Normalised deviation was used to measure the performance of each candidate plan within the uncertainty space in the context of the parameters used. The normalised deviation results in Figure 4-6 are used to interpret the performance results for each plan across the measures. Out of the 76 IPs yielded through the multi-objective optimization, 30 achieved over 95% security of supply. Figure 4-6 shows the normalised deviation analysis for these 30 IPs. Each bar represents a single strategy, stacked by the deviation from the most optimal candidate strategy in each of the three performance metrics. The shorter bars the bars the more robust the performance. The figure allows the visualization of the magnitude of deviation for each solution across the three performance metrics. An ideal performance in Figure 4-6 would be a bar that intersects the vertical axes at zero for all of the metrics. It is important to note that each of the metrics has been given equal weighing for the deviation analysis, and that with different weighing the results would differ.

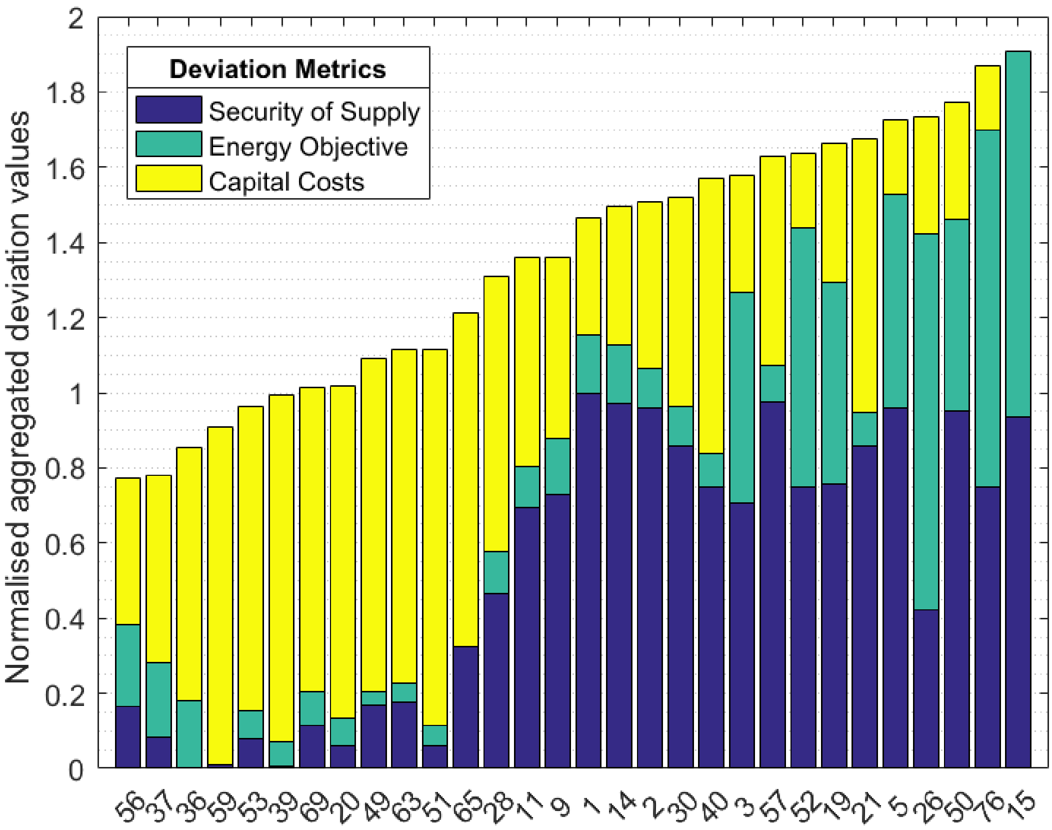

Figure 4-6. Normalised aggregated deviation analysis results

As can be seen, IP56 exhibits the lowest deviation overall, closely followed by IP37 and IP36. These three IPs all include large effluent reuse schemes as the main infrastructure option, in conjunction with other small infrastructure supply options. These IPs have relatively low upfront capital expenditure, with high security of supply and moderate operational energy costs. Therefore, based on equal weighting of the three criteria, IP56 would be chosen as a candidate strategy to continue the RDM process. Because water utilities work in five-year investment cycles it could be harder to argue high short-term capital investments for very long-term (20-year) benefit horizons, than smaller up-front capital investments. Nonetheless, as mentioned above, the 2014 Thames Water WRMP, included a large wastewater re-use facility within the Preferred Plan for the medium to long-term options for water supply, as well as small groundwater schemes and the development of a canal, just like IPs 36 and 37.

The water sector has started to consider the longer-term implications of water resources, and planning is now also occurring in 25 and 80-year plus time horizons, as well as beginning to incorporate the concept of flexible ‘adaptive pathways’. The model has the potential to accommodate this extended period and adaptive strategies. Such paradigm shifts in planning will enable more flexible plans to reduce lock-in to large infrastructure projects that may not be needed, and tools that can inform on detailed interdependencies with other sectors, like this study is starting to do, will be invaluable to provide useful information within such frameworks.

4.3.3 Uncertainty analysis for candidate strategy

Having identified a candidate strategy, the performance of that strategy was scrutinised under the 270,000 scenarios. Figure 4-7 shows the performance of IP56 under all states of the future considered, capturing the uncertainty in per capita demand, population change and water availability in each axis. The figure is coloured by the security of supply. Each dot represents a scenario with an associated security of supply. A combination of moderate to high per capita demand (PCD) combined with high population growth and low water availability lead to lower security. PCD has the highest influence on the performance of the particular portfolio, as can be noted on the Figure, where the scenarios with higher PCD have a larger number of lower security of supply values (Figure 4-7).

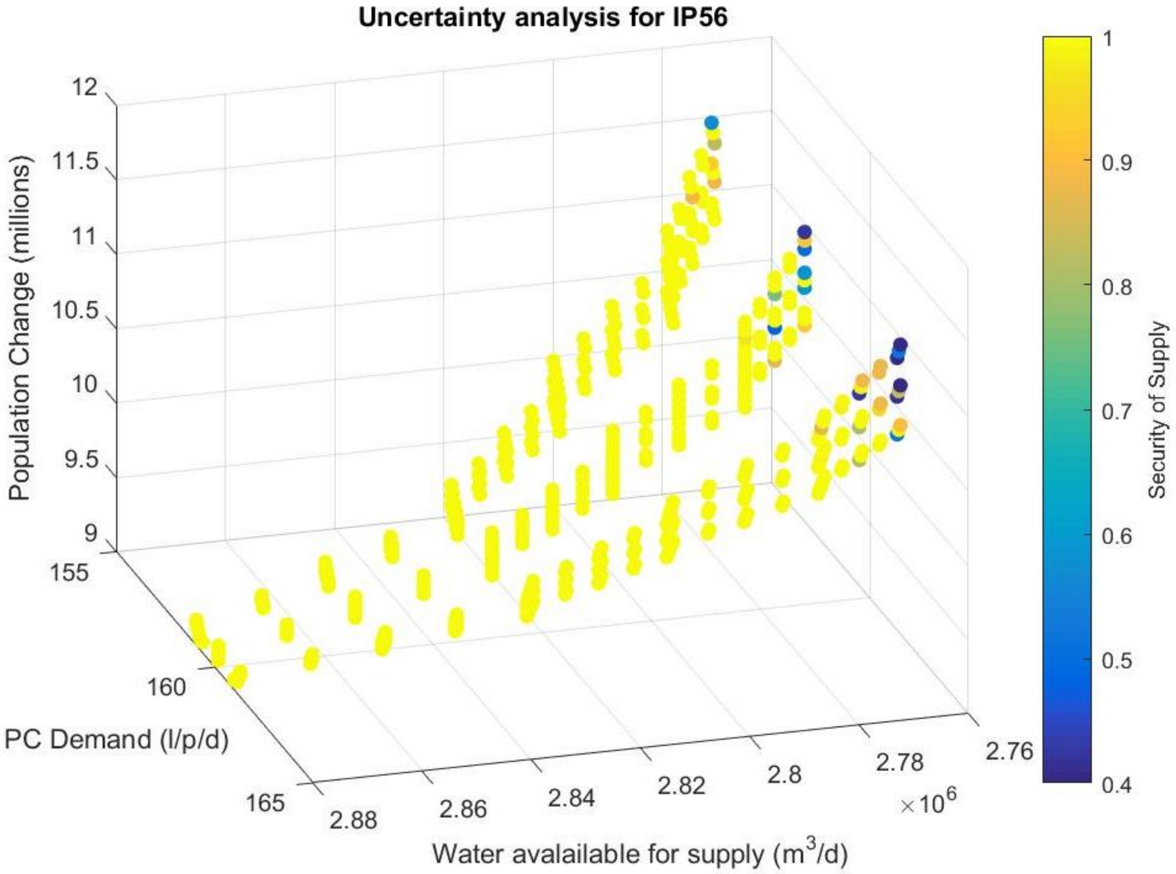

Figure 4-7. Uncertainty analysis for security of supply for selected plan

If any of the vulnerable conditions were to emerge, alternative strategies would be preferred over IP56. For example, IP36 and IP39 have double the upfront capital investment costs but provide the highest robustness to the range of uncertain futures explored. Thus, the more likely reductions in water availability, large increases in population and no decreases in per capita demand are, the more necessary additional investment may be to ensure security of supply of supply. How much additional investment would be needed will depend mainly upon reductions in per capita demand. As noted previously, other IPs that included demand management as an option could be more robust to changes in per capita demand, reducing the vulnerability of the system. It should be noted that Thames Water, as all English and Welsh water companies, is already making progress in demand management options as a default response in the short-term, reflecting the planning process requiring such approaches to be actively delivered.

The results show that in the context of the adopted parameters and constraints that without the consideration of operational energy costs, other strategies would have emerged as more desirable, but would have had significantly higher costs in the long-term. For example, IPs such as 26, which provides a modelled security of supply of over 95% but would incur over 4 times the assumed operational energy costs in the long-term. Figure 4-8 shows the uncertainty analysis of the operational energy costs for IP56. It shows the three uncertainty elements included in the model on the axes and the monthly energy costs for each of the future states tested in GWh per month. The colour bar reflects the monthly energy costs in GWh. Energy costs are highest in scenarios with high per capita demand and low water availability, most likely due to infrastructure that has to be used at full capacity and existing options that are expensive to run have to be used. As discussed above, coupling the IP56 with shorter-term demand management schemes could reduce the vulnerability of the system to incurring high energy costs.

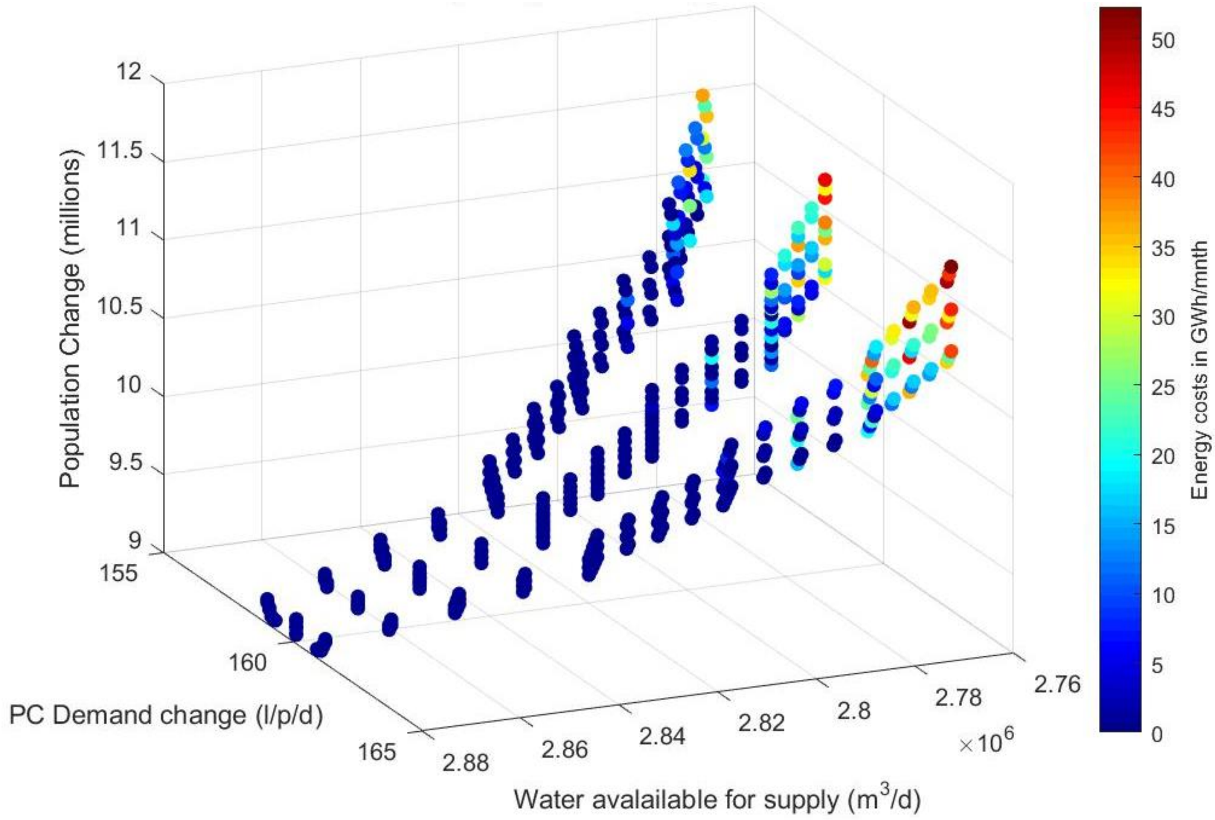

Figure 4-8: IP56 uncertainty analysis for energy costs (GWh/month)

Figure 4-8 provides a visualization of how energy costs may change under certain conditions within the basin, which can help quantify costs more in detail and evaluate risks for future scenarios, not just for providing enough water but also of the energy costs associated to exogenous pressures. It can also provide a partial quantification tool to help assess the long-term impact of energy efficiency, additional watershed management or governance approaches that reduce the energy intensity of current infrastructure.

Further iterations of the RDM analysis could go on to identify the specific vulnerabilities of other IPs and compare them based on which vulnerabilities are more significant or probable by proposing incremental improvements to this candidate strategy, which can then be compared through energy costs to evaluate what costs savings there could be from incremental improvements, if any. As detailed in Matrosov et al. (2013), if probabilistic information is available, this information can be used to generate other sets of plausible futures to judge whether these probabilities should be hedged against. These steps would be repeated until a satisfactory robust strategy has been achieved.

This study provides a framework that could help support existing decision-making processes for preferred options, by visualizing potential energy costs of preferred options and quantifying their uncertainty. Comparing the solutions with the Thames Water least-cost plan shows that the results of their analysis and of the analysis in this study align closely. The WRMP 2014 preferred plan for the TW region implements demand management, small groundwater schemes, a canal and wastewater re-use in the long-term. In this study, small groundwater, demand management and wastewater reuse schemes rather than a canal, emerge within the preferred portfolios. There is continued uncertainty around the range of exogenous pressures considered in this model, so these will be areas of continuing uncertainty that need to be evaluated in detail, and which could result in changes in the outputs. This study has created a potential basis for developing more sophisticated tools that could consider uncertainty of energy costs and wider operational costs in the long-term water resources planning framework, which could be incorporated within the wider decision-making process. Ultimately, this may allow decision makers to use such scenarios to inform discussions of what factors are most important for future planning. They could quantify the energy costs incurred under varying future states and quantify which alternative options can provide more cost savings in scenarios of vulnerability to increased costs.

4.3.4 Benefits and limitations of approach

The aim of the model was to inform water resources decision-making processes about potential energy implications of different water supply and demand management options. Although the model achieved this, it did not consider all the elements included in long-term resources planning approach used by UK water utilities. For example, the model did not consider severity of restrictions or detailed deliverability factors. Therefore, the conclusions drawn from the model cannot be taken in isolation, but they can be used to illustrate how such a candidate model can provide additional information to consider when making decisions about options, specifically within an RDM framework and multi-objective optimization. Rather than producing a definitive set of least-cost implementation options, the Water-Energy model and RDM application show how consideration of long-term energy costs in a robust assessment could provide useful information to supplement other conventional water resource planning decision-making tools. The multi-objective optimization shows how optimization techniques can be used to incorporate energy costs, and other elements, into long-term water resources planning.

The model does not consider elements of acceptability, deliverability or licence conditions of options, and thus should be taken as a supplementary tool to support decision-makers when they are trying to incorporate long-term energy costs into water resources management. The model is by necessity a simplified representation of the Thames system. This is in part because a more detailed system representation would incur higher run times and would be outside the scope of this project, which was to demonstrate the potential usefulness of using an RDM framework and multi-objective optimization to incorporate detailed energy costs into long term water resources planning. This also meant that there was a limit to the number of alternative plans that could be considered, as well as the uncertainty variables that could be incorporated and the detail with which each portfolio was built. There is also influence from human decision-making and investment cycles when making decisions for new infrastructure, such as the UK 5-year decision cycle which may influence how and when new investments are made within a company, which was not considered in the model. There may be other external factors and uncertainties that the solutions are sensitive to that are external to the boundaries of what has been included in this study, particularly within longer-term frameworks. Energy prices or pump efficiencies, would be some of these, which could be considered as uncertainties in future iterations of the model.

However, the RDM approach with multi-objective optimization used in this study does offer various benefits. The approach allows for several objectives to be tested at the same time, offering flexibility in application to water resources problems that usually have competing objectives. The optimization approach permits the finding of near-optimal portfolios for the criteria adopted that can be robust under multiple scenarios. The approach allows the visualisation of the trade-off between water and energy objectives simultaneously allows decision-makers to understand trends and properties of the system. Trade-offs between capital and operational expenditure for example, showed that most options will incur high capital or operational expenditure to guarantee high security of supply. The MORDM framework also permitted a visualization of both a traditional robustness measure, security of supply, with associated energy costs within an uncertainty space for a candidate strategy, which can assist decision-makers to make robust decisions.

The normalised deviation analysis examined the performance of IPs across multiple futures and compares their performance in three metrics visually. The exercise also helped identify IPs that had high deviation in the metrics which could be discarded, thereby reducing the number of solutions to choose from and enabling the decision-maker to ultimately choose a strategy that is robust to uncertainties.

The treatment of uncertainty provides an understanding of the performance of a preferred plan and how the uncertainties stress the proposed system, producing tangible performance metrics. For example, in examining how uncertainties affect the energy costs of the candidate strategy, decision makers can hedge against extreme scenarios by developing additional elements to proof chosen strategies. In the case of our candidate strategy for example, the energy consumption increased significantly under scenarios of high per capita demand, which points towards developing per capita demand management in order to avoid high costs.

4.4 Conclusions

Water resource planning is widely regarded as a problem of decision making under uncertainty. The planning problem is conventionally framed as one of selecting least cost options to achieve the desired security of supply. However, whilst energy costs represent one of the greatest operational cost of a water utility (second after staff costs in the UK) the changing nature of energy use in water resource systems has not been explored on a sound empirical basis. The Water-

Energy Model was introduced, which includes the relative significance, as well as trends in energy consumption, from all components of the urban water supply system.

The multi-objective Robust Decision Making analysis showed that to increase security of supply in the water resource region, the options generally become more expensive. When long-term costs are not considered, portfolios with high security of supply, but potentially high operational energy expenditure could be the most attractive. However, there is inevitably a trade-off between meeting water delivery objectives and reducing energy costs, as more infrastructure increases energy consumption. The deviation analysis showed that using less supply-side measures and more demand management measures ensures lower-cost lower-regret measures. The best performing portfolio included a large effluent reuse plant, highlighting the benefits of water reuse. The uncertainty analysis showed that to reduce vulnerabilities in the chosen strategy however, demand management focused on reducing per capita demand could reduce the vulnerabilities of the strategy in the long-term, both in security of supply and in energy costs. Pre-emptive actions will need to be taken well before such measures may be needed. Within a long-term frame, the study has shown that implementation of a robust adaptive strategy to supply water could be helped by an evaluation of energy costs of possible supply and demand options.

5. Quantifying the energy costs and greenhouse gas emissions of changing wastewater quality standards

5.1 Introduction

The discharge of untreated wastewater from urban areas into waterways has significant detrimental effects on ecosystems and potentially also human health. Therefore, regulations to ensure adequate treatment are becoming more stringent as the negative effects of different pollutants on humans and the environment are understood. Water quality measurement technologies are also becoming more cost-effective, which is enhancing understanding of the extent of pollutants in the aquatic environment.

To meet the requirements of the Water Framework Directive (WFD), which is the EU legislation for ground and surface waters, regulation of effluent discharges from waste water treatment works and other industrial plants has become more stringent (A. Marsh, Vale, and Watson 2002). The WFD aimed for member states of the European Union to achieve 'good status' of their water bodies by 2015. The UK has made considerable progress to achieving this status, but it is still far from meeting the legally binding EU water pollution targets by the second management cycle, which extends to 2021, six years after the initial deadline (Voulvoulis, Arpon, and Giakoumis 2017). Further tightening of effluent standards is therefore possible in the future.

Maintaining and improving water quality in the face of population growth and climate change pressures will be an ongoing challenge for the water sector. Climate change has the potential to impact water management objectives by altering water quantity, temperature, quality and freshwater biodiversity (Arnell et al. 2015). As people become wealthier and expectations change, there is likely to be greater demand from water users for environmental improvements. This is likely to be reflected in increased environmental standards over time (Ofwat 2015). Furthermore, EurEau, the European association of the water service sector, believes that there have been insufficient measures to protect drinking water so far (Barker et al. 2015). This means that further regulation to protect drinking water sources can be expected in the second period of the WFD.

As effluent standards change and become more stringent, higher plant investment and operation costs will be incurred. This is coupled with necessary capacity increases to cater for increasing populations, and projections of more extreme rainfall events (Burt et al. 2016). More advanced treatment processes can lead to increases in power consumption and may require more chemical loading for treatment, which in turn leads to increases in financial costs and greenhouse gas emissions (Gu et al. 2016). In fact, according to the WssTP (2011), increasing standards for discharges from wastewater treatment have led to a doubling of energy use in WWT in the UK between 1990 and 2011, and this is projected to double again in the next 15 years. Increasing effluent quality standards are widely believed to be the largest cause of rising carbon emissions in wastewater treatment (Water UK 2008b; Baleta and Mcdonnell 2012).

Even though there is recognition that increased energy costs and carbon emissions will be incurred, there is little work that has been undertaken to quantify specific or potential future costs. According to Sadler, Georges and Thornton, (2009) there have been no detailed investigations of potential treatment requirements associated with Water Framework Directive standards. Some theoretical work has been carried out, particularly on carbon footprints

(Barber 2009; A. Marsh, Vale, and Watson 2002; Sadler, Georges, and Thornton 2009), mostly concluding that aeration accounts for the largest contribution to the carbon footprint of wastewater treatment.

In this context, there remains a tension between different pieces of environmental legislation in most countries worldwide. On the one hand, the aim to improve the environment by driving up standards in the wastewater sector, and on the other hand, reducing anthropogenic greenhouse gases that drive climate change targets. In the UK this tension manifests itself as a tension between EU legislation, including the WFD and the Urban Waste Water Treatment Directive, and the UK Climate Change Act of 2008. This has already led to authors suggesting the need to address these conflicting demands effectively (Baleta and Mcdonnell 2012; Parsons and Marcet 2012). Decarbonization of electricity supply is already occurring which will reduce the carbon footprint of wastewater treatment, but at the moment 75.5% of global electricity supply is still generated from fossil fuels. Even when decarbonization of the electricity sector is complete, electricity will continue to represent a major operational cost burden for water utilities.

Using operational data from six Wastewater Treatment Works (WWTWs) in the London region, operated by Thames Water, that have undergone significant expansions to deal with increasingly stringent effluent standards, this study aims to quantify the potential future costs and greenhouse gas emissions of such effluent standard increases in the UK. To address this objective, an empirical model is estimated from observations of the relationship between pollution removal and energy consumption in large WWTWs. The model is then used to test scenarios to understand the potential costs and greenhouse gas implications for the UK. The study addresses four measurements of pollution that are monitored in large WWTWs and by the EU WFD. These are Biochemical Oxygen Demand (BOD), Ammoniacal Nitrogen (NH_3-N), Suspended Solids (SSs) and Chemical Oxygen Demand (COD). The use of empirical data on actual plant energy use is revealing compared to previous estimates of the costs of achieving improved effluent standards, which have been based on more theoretical estimates and data on idealised plant performance (UKWIR 2015). Moreover, for the first time we have been able to relate observed energy use with effluent water quality monitoring for four indicators of water quality.

5.2 Materials and methods

5.2.1 Methodological approach

Between the periods of 2010-2015 the energy use of all wastewater treatment in Thames Water almost doubled, also adding over 25% to the company's overall energy bill. Previous analysis found that WWT is approximately 50% of total sector electricity consumption (Cardenes et al. 2017). The increase in WWT energy consumption is almost solely due to new extensions built in five main wastewater treatment works in London to meet higher demands and new standards. Due to data limitations one of these WWTWs is not included in this analysis, but two other large Wastewater Treatment Works (WWTWs) in London are used to complement the dataset. The dots in Figure 5-1 show the location and relative size of the six WWTWs in London included in the analysis. These WWTWs have similar standards for effluent discharges (there are slight differences depending on the river section on which they are located), which are expected to continue to increase in the future (Defra 2012a; Defra 2008). The four main types of extensions that have been added to the WWTWs to improve the quality of effluent include inlets, PSTs, ASPs and/or FSTs.

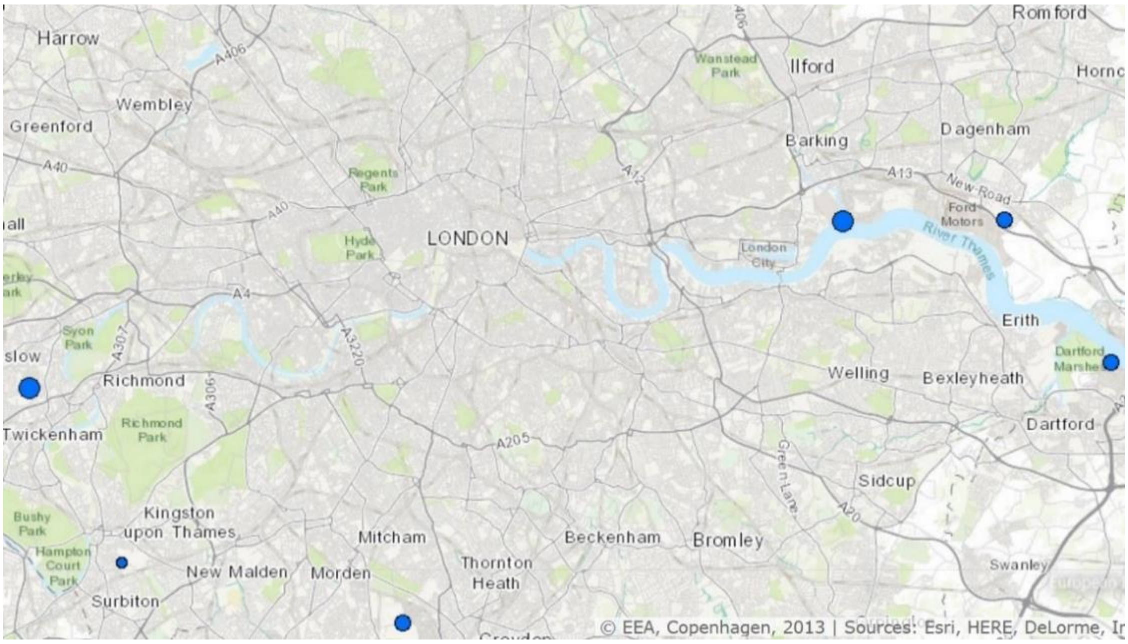

Figure 5-1: Map showing the location and relative size of the six WWTWs under study (European Environment Agency 2014)

A robust linear regression analysis was performed to establish whether there was a statistical relationship between electricity consumption at the WWTWs and the extensions installed to meet new standards and the amount of pollution removed. This approach has been used in similar studies investigating energy consumption at WWTWs (Longo et al. 2016; Carlson and Walburger 2007). Extensions are defined as an addition to a plant of the four types described above (inlets, PSTs, ASPs and FSTs) built in a WWTW. In the regression model, the extension installations are included in the month when the extension went online (started treating sewage), and are represented as the amount of additional flow being treated at the works by this extension, as a percentage of the flow. In this way, we can not only capture the energy implications of installing new technologies at WWTWs but also begin to estimate how much specific amounts of additional treatment might cost in the future.

The amount of pollution removed is represented in the form of four key pollution measures to be reduced at the WWTWs: Biochemical Oxygen Demand (BOD), Ammoniacal Nitrogen (NH_3-N), Suspended Solids (SSs) and Chemical Oxygen Demand (COD). They are aggregated into a composite pollution load indicator as has been done in previous studies (Rodriguez-Garcia et al. 2011; Longo et al. 2016; Feng and Chen 2016). This was done because the pollution loads are strongly correlated with each other, thus transforming them into one composite indicator allows the model to be more robust and avoid autocorrelation outputs. Load in the influent to the WWTW is defined as the weight of the relevant pollutant (in kg) calculated from its concentration (in mg/l) multiplied by the incoming wastewater flow (in m^3) at the WWTW when the sample was taken. The conversion to load is important because all the plants under study are preceded by combined sewer systems (conveying both sewage and storm-water) and thus the effect of dilution is relevant.

The elements of the index were weighed according to the relative energy it takes to treat a kg of each, as indicated by wastewater experts in the sector (Thames Water wastewater expert, personal communication, 20th May 2017). Ammoniacal nitrogen was the most significant, as it takes four times the oxygen to treat a kg of ammonia than a kg of BOD. COD was removed as it represents the same measure as BOD (in terms of the energy needed to treat them), so including it would have double counted energy consumption. Finally, SS is the least significant in terms of the energy it takes to remove, as most SS settles out in primary settlement tanks, and little of what is left reaches aeration plants.

Thus, the SS was left at its original measure. Sensitivity analysis was carried out on the index components to evaluate the influence of changing the weighing of on the results. Consequently, the Weighed Pollution Load Removal Index was defined as follows:

$$PLR= ((BOD\mathit{i} – BOD\mathit{o})*2 + (NH_3\mathit{i} – NH_3\mathit{o})*8 + (SS\mathit{i} – SS\mathit{o}))*WW\mathit{flow} \quad (1)$$

where PLR stands for Pollution Load Removal Index in kg, *i* indicates the incoming pollution concentration in mg/l at the WWTW and *o* indicates the outgoing concentration in mg/l at the WWTW outlet. The pollution load is then calculated by converting to m^3 and multiplying the amount of pollution removed by the flow received at the WWTW in m^3 (WW*flow)*. Thus, the resulting composite indicator reports the average pollution load removed at each WWTW monthly.

The analysis was carried out jointly for all WWTWs as it was assumed that relationships would hold across WWTWs (Benedetti et al. 2013). Robust regression is applied because the residual distribution of the data was prone to outliers, thus invalidating standard linear regression assumptions. The robust fitting method is less sensitive than ordinary least squares to large changes in small parts of the data and was thus appropriate. After several iterations and variables were considered, the model was established as follows:

$$E = \beta_0 + PLR + Inlet + PST + ASP + FST + \varepsilon \quad (2)$$

where β_0 represents the intercept, *E* is the total energy use in kWh in *N* plants, PLR represents the contribution to the energy consumption from the Pollution Load Removal Index described above; Inlet, PST, ASP and FST represent the regression factors for the type of extension/technology and additional load treated in it at N plants, and ε is the error term.

The four types of extension (inlets, PSTs, ASPs and FSTs) were initially considered in the model iterations as equation (2) above shows. However, the installation of inlets, primary settlement tanks and final settlement tanks did not have a significant correlation with energy consumption. Additional aeration lanes did have a very significant effect on the energy consumption, and thus this variable was used in the final model.

5.2.2 Scenario selection

Once the model was built, three scenarios of more stringent effluent quality standards were established. Potential energy costs (kWh) and GHG emissions from meeting these standards were estimated to establish their potential impacts on the UK water sector. As the sample of the WWTWs included works that are all the largest denomination in Europe (over 150,000 population equivalent (p.e.) served), the costs were up-scaled to the 101 WWTWs in the UK that are of comparable size. These 101 works serve 59% of the UK population, and have capacity to serve another 20%. Three more stringent effluent standard scenarios were chosen to evaluate how the cost of removing pollutants to a higher level might influence the energy consumption of the treatment work (Table 5-1). The addition of aeration processes to the WWTW was also tested in the scenarios as their addition was found to significantly impact the energy consumption of the WWTWs. Thus, the proportion of ASP that was added to each scenario can also be seen in Table 5-1.

Barber (2012) used similar scenarios to test how more stringent standards might influence the electricity consumption and operational greenhouse gas emissions of a theoretical WWTW, but did not include COD. Marsh, Vale and Watson's (2002) set out benchmark values for high quality effluent, which are used in Scenario C. The final scenario standards were derived from the two publications and UK Technical Advisory Group on the Water Framework Directive recommendations (UK TAG 2013), then discussed with sector experts and summarised as follows:

Table 5-1: Scenario standards adapted from Barber (2012) and Marsh et al. (2002) and extensions to WWTWs in the scenarios

Scenario/ Pollutant (mg/l)	Current average standards*	Scenario A	Scenario B	Scenario C
Biochemical Oxygen Demand (BOD)	22	20	10	5
Ammoniacal Nitrogen (NH_3-N)	8	6	4	1
Suspended Solids (SSs)	25	15	10	5
Chemical Oxygen Demand (COD)	No current standards	50	30	20
Extensions to WWTWs to meet standards				
New ASPs	NA	ASP for 20% of flow	ASP for 40% of flow	ASP for 60% of flow

*may vary slightly between specific WWTWs.

The current average standards for BOD and SS are representative of the Tidal Thames WWTW standards, where most of the sampled works are found, while AmmN standards can be slightly higher. The three scenario standards were applied to three representative WWTWs of different capacities to evaluate the energy consumption across sizes. The defined sizes represent a range of medium to large WWTWs such as the sample represented in our model, of 400ML/day, 600ML/day and 800ML/day.

There are 9 resulting scenarios that combine the three pollution standard scenarios and extensions with the three WWTW sizes. The PLR is recalculated for each scenario using eq. (1) above to obtain the resulting energy consumption from having to have higher quality outgoing effluent. In this iteration, the empirical outgoing pollution concentrations are substituted by the scenario figures in Table 5-1 to calculate the pollution load that would have to be removed under each scenario. The incoming pollution data remains the same as in the empirical dataset. These figures are then converted to load as in eq. (1) with the scenario WWTW sizes.

5.2.3 Upscaling to implications for the UK

The UK has 101 WWTWs that serve 150,000 people and over, the largest size denominator in Europe for WWTWs. This data is used to make an estimation of the potential UK-wide annual electricity costs from meeting higher effluent standards.

The electricity cost estimates are then converted to potential GHG emissions. The current UK electricity conversion factor of 0.412 $kgCO_2e$ per kWh is used. Alternative future emissions factors are also used to calculate the potential GHG emissions, due to likely grid decarbonization futures. The Committee on Climate Change sets out scenarios for the Fifth Carbon Budget, including the central scenario (0.18 $kgCO_2e/kWh$), which is their best assessment of the technologies and behaviours required to meet targets and the barriers scenario (0.25 $kgCO_2e/kWh$), which represents less favourable conditions (Committee on Climate Change 2015). This results in three scenarios of grid electricity intensity that are compared to the three effluent standard futures to result in a range of emissions. The conversion applied is as follows:

$$MTCO_2 = (101*E_C)*C*12/10^9 \qquad (3)$$

where E_c is the mean monthly energy consumption (in kWh/month) by scenario, multiplied by C, the GHG conversion factor (in $kgCO_2/kWh$) and annualized, then converted into $MTCO_2$, and scaled by the number of similar sized WWTWs in the UK, to obtain the estimated GHG emissions that could result from three scenarios of more stringent effluent quality standards.

5.3 Results

Figure 5-2 shows three timelines: the wastewater flows time series of the WWTWs in the study, the energy consumption over the same period and the extensions that were built in the sample WWTWs over the same period. The third timeline show what type of plant expansions were installed as well as the specific points in time when they came online. Each shape size represents the number of that type of extension built, and the number within the circle represents how many. Each line represents a different type of technological expansion, either new inlets, PSTs, ASPs or FSTs. As can be noted, there is no increase in the average wastewater flow over the sample period, but there is a sharp increase in the overall energy consumption of the WWTWs, which matches when the first extensions come online, and by 2014 the monthly energy consumption of the 6 WWTWs has doubled. The figure illustrates that there is variability in energy use, but notwithstanding the variability, there is a clear signal associated with plant expansion. Furthermore, as the wastewater flows time series on the first timeseries shows, there is no change in the average wastewater flows being treated at the WWTWs, pointing to the fact that the increases in energy consumption can be attributed to the plant expansions.

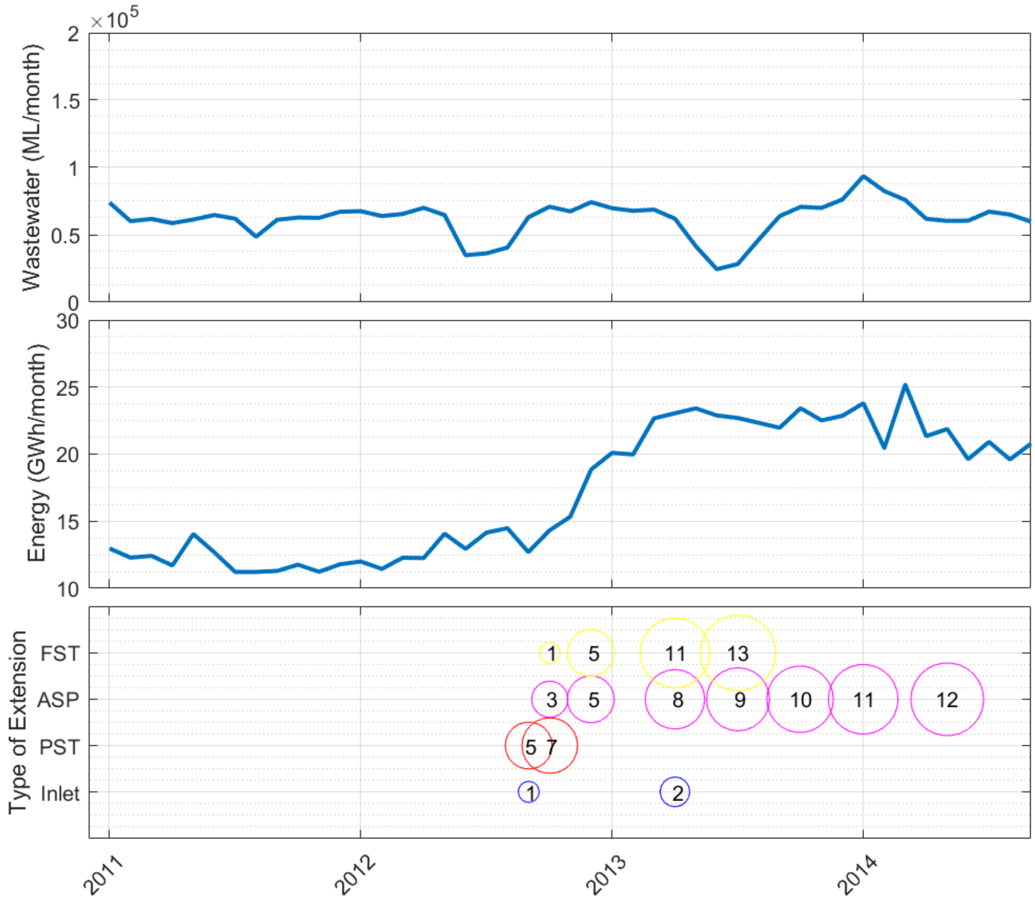

Figure 5-2: Energy consumption and wastewater flows of WWTWs under study with plant extensions

Figure 5-3 shows the statistically significant relationship (correlation coefficient 0.856) between energy use and the Pollution Removal Index (PLR). As can be observed, the more pollution is removed the higher the energy consumption. A logarithmic transformation is applied to the scatter plot to account for the range in infrastructure sizes, as has been done previously in studies dealing with large WWTWs (Carlson and Walburger 2007). The larger energy numbers account for the larger WWTWs and the smaller numbers for the smaller WWTWs, where there is slightly more variance. If the sample contained more WWTWs of the middle sizes the sample points would be more continuous.

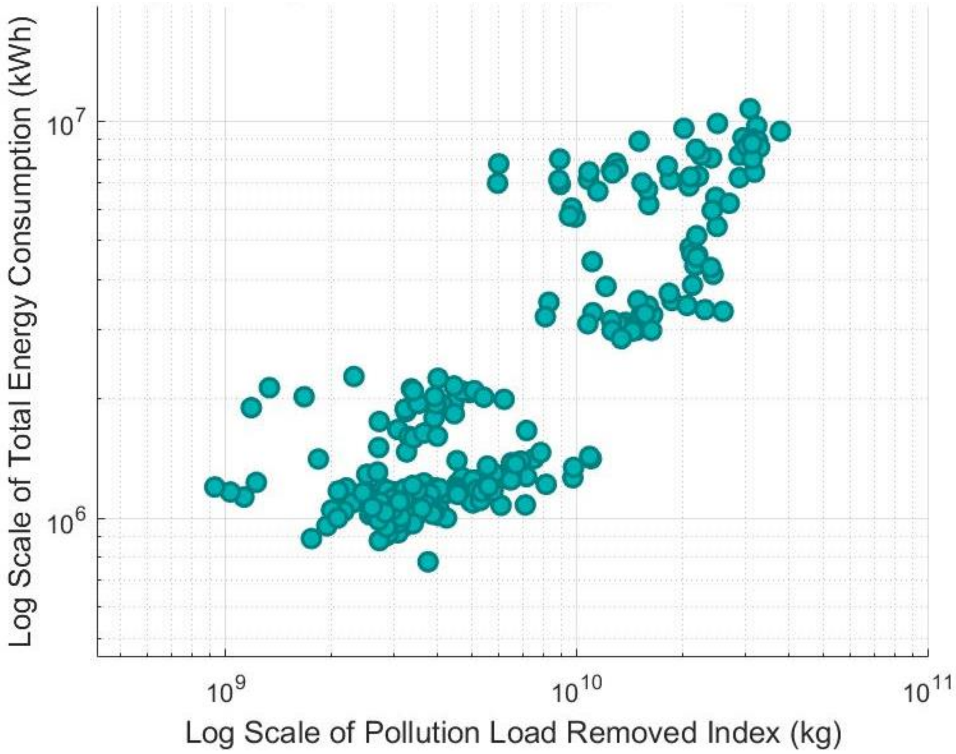

Figure 5-3: Correlation between average PLR and energy consumption at WWTWs.

Using equations 1 and 2 above for the relationship between energy and PLR and energy and WWTW technological extensions, a final regression model was built to quantify the relationship between pollution removal, specific types of plant extensions and energy consumption. The final model that represents energy use as a function of the removal of four key pollutants, water flow (in the form of load) and the type of technological extension built to treat wastewater to a higher quality is shown in Table 5-2. The model explains over 95% of the energy use variation as noted by the adjusted R^2 correlation statistic, it is also a highly statistically significant model as denoted by each predictor's p-value and the overall model p-value. The t-statistic values show that the independent variables are a very good fit. As can be seen in the table, the final model shows that the variance in energy consumption is mostly determined by the amount of pollution load removed, as well as the installation of additional activated sludge processes.

Table 5-2: Robust linear regression model results

Estimated Coefficients:	**Estimate**	**SE**	**tStat**	**pValue**
Intercept (β_0)	$-4.06*10^6$	$1.94*10^5$	-20.91	0.000
Activated sludge processes (ASP)	45759	$1.88*10^3$	24.30	0.000
Pollution Removal Index (PLR)	0.0002	$3.97*10^{-6}$	43.91	0.000

Number of observations: 239; Error degrees of freedom: 236; Root Mean Squared Error: 4.59e+05: R-squared: 0.951; Adjusted R-Squared **0.951**; F-statistic vs. constant model: 2.31e+03; p-value: 0.000.

The final linear regression model (robust fit) is thus:

$$\text{Energy Consumption} = \beta_0 + \text{ASP} + \text{PLR} + \varepsilon \qquad (4)$$

Where β_0 represents the intercept, ASP represents the Activated Sludge Process technology added, PLR represents the Pollution Removal Index and ε represents the error term, which in the scenario predictions is represented as the randomized standardized error from the empirical data. The final regression model is used to predict the energy consumption of wastewater treatment in the UK under changing effluent standards for a set of scenarios.

5.3.1 Scenario results

Figure 5-4 shows the monthly energy consumption for the scenario sample WWTWs under the Scenarios A, B and C of more stringent effluent quality standards for each of the three sizes of works. The boxplots represent the median energy values in GWh per month for each WWTW. The tops and bottoms of each 'box' represent the 25th and 75th percentiles of the results, respectively. The dot represents the median, the vertical lines represent the furthest observations within 1.5 interquartile range and observations beyond are outliers. The first boxplot represents current empirical energy consumption. Each set of three boxplots thereafter represents Scenario A, B or C, and the order in which they're shown represent the three sizes of works, small, medium and large. As can be seen, the size of a WWTW has a large influence on the energy consumption of the treatment works. However, the more stringent standards in each scenario also result in increasing energy consumption with higher effluent quality requirements. It can also be noted in the boxplot that both in the actual data sample and in the modelled results there are quite a few high-energy consumption outliers due to some months of the sample having particularly large contamination loads to be removed. These are most likely due to drier conditions leading to higher concentrations of pollution in specific months, thus leading to some variability in the energy costs of removing the pollutants. It is also noteworthy that the current distribution is skewed whereas the projections are more symmetrical, apart from the outliers, because linear regression assumes a gaussian distribution in the projections.

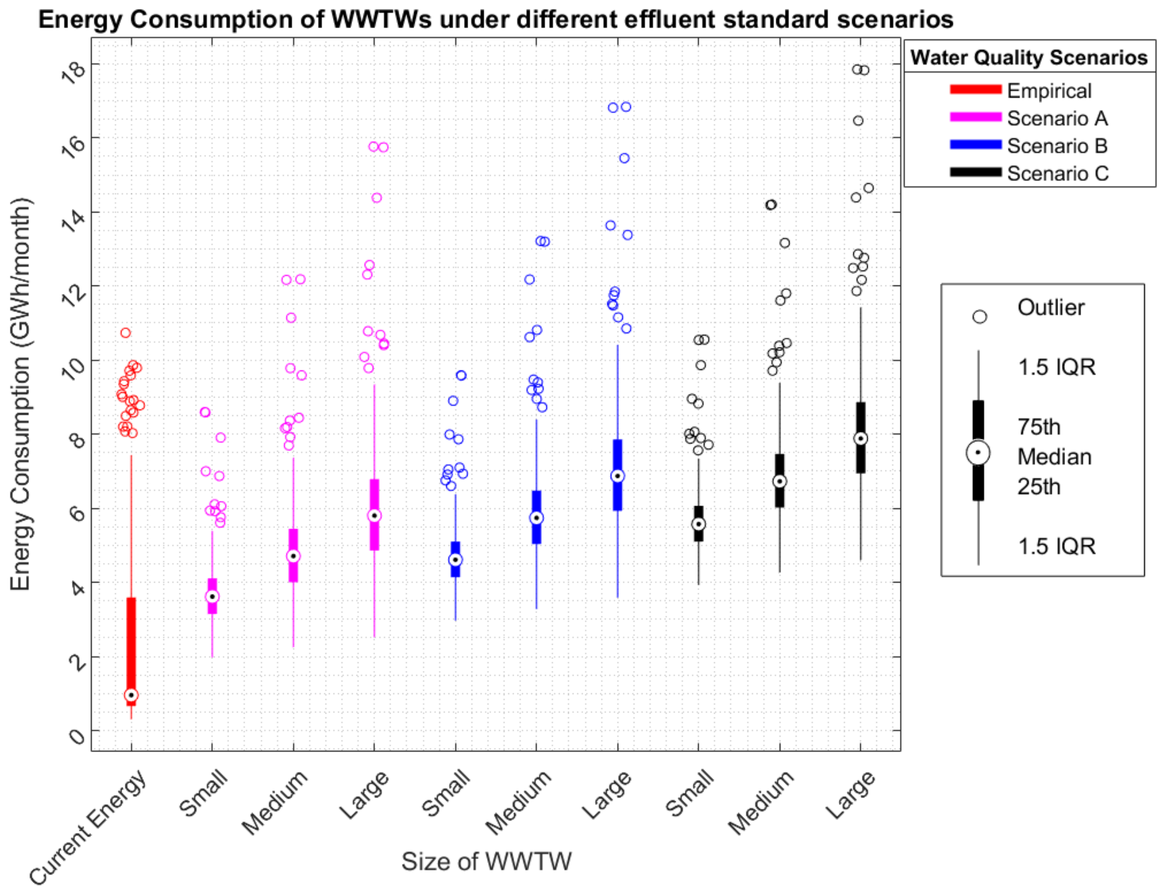

Figure 5-4: Energy consumption of each WWTW under scenarios of increasing effluent standards and three medium-to-large WWTW sizes.

5.3.2 Up-scaling results

The electricity consumption of the sample WWTWs in the case study doubled over the period between 2010-2015. The results show that on average energy consumption in large WWTWs for the whole of the UK could further increase by 3,147, 4,397 and 5,593 GWh per year to meet more stringent effluent standards (subject to baseline consents), ranging in a percentage increase of between 112% and 211%. Table 5-3 shows the total increases for energy consumption, derived from the regression model (equation 4), alongside the corresponding GHG emissions, derived from equation 3. In terms of GHG emissions, the $MTCO_2$ emitted will depend on the composition of energy sources in the grid. Using the three scenarios of decarbonisation described above, Table

5-3 shows the average potential range of emissions under each of the more stringent effluent standard scenarios versus the grid decarbonisation scenarios.

Table 5-3: Regression model results: energy consumption (GWh/year) and GHG emissions (MTCO$_2$/year) from more stringent effluent standards against grid electricity intensity factors

Effluent Standards	**Current Standards**	**Scenario A**	**Scenario B**	**Scenario C**
Average energy consumption (GWh/year)				
GWh/year	2805.9	5953.3	7203.1	8399.7
Carbon emissions factor	**Average GHG emissions (MTCO$_2$/year)**			
Current 0.41 kgCO$_2$e/kWh	1.15	2.43	2.94	3.42
Barriers Scenario 2020 0.25 kgCO$_2$e/kWh	0.70	1.49	1.80	2.10
Central Scenario 2020 0.18 kgCO$_2$e/kWh	0.51	1.07	1.30	1.51

The results show that more decarbonised futures somewhat offset the increase in emissions from more stringent standards. There are 0.51-1.51 annual MTCO$_2$ emitted under the most decarbonised grid, versus a range of 1.15-3.42 under current emissions factors. However, even with the lower effluent standards and the best mix of energy sources in the grid there could still be over 0.5 MTCO$_2$ emitted annually from changing effluent standards towards 2020 (depending on the emissions factor). Taking into account that according to the latest UK statistics, the waste management sector (which includes the wastewater sector) emitted just over 18 MTCO$_2$ of the 495 MTCO$_2$ emitted in the UK in 2015 (BEIS 2017), such increases could be very significant.

It is important to know that these calculations would only concern the large WWTWs in the UK, which have the capacity to treat wastewater for the population equivalent of approximately 53 million (EEA 2015). There are 1896 WWTWs in the UK, and while the remaining 1795 WWTWs are of smaller size with an average size of 25 ML/day (and a combined treatment capacity of 37 million p.e.), meeting more stringent effluent standards at these smaller works will also require larger quantities of energy, especially as smaller works do not benefit from economies of scale. Furthermore, this study only considers increases in the direct operational energy and emissions from WWTWs. Even though studies have found that operational emissions from electricity consumption are the largest and most significant at WWTWs, there are other indirect costs and implications from tighter effluent standards, such as more direct emissions from the processes themselves, that are not included in this study.

5.4 Discussion

The final model results show a very significant relationship between pollution removed at a WWTW and the energy consumed. This is coupled with the finding that the addition of more treatment in the form of activated sludge processes has a very strong impact on the energy consumption of the works.

We note that alongside increasing nitrogen and phosphorus standards, more stringent standards for other emerging contaminants (ECs), such as metaldehyde, hormones or pharmaceutical products, are to be expected, potentially requiring even more energy intensive technologies to remove difficult pollutants. Current state of the art WWTWs have not been designed for the removal of ECs and additional infrastructure will be needed (Sichel, Garcia, and Andre 2011). Technologies can include advanced oxidation processes, ozonation, activated carbon, or membrane technologies, which will all incur significant capital and operational costs. Raghav *et al.* (2013) suggested that removing ECs of concern is technically possible, but extremely energy intensive. Further work is still needed to understand the long-term environmental and health effects of ECs in order to evaluate whether costly investments and their associated energy and greenhouse gases would be justifiable.

Previous studies have recognised aeration as one of the largest energy consumers within wastewater treatment (Caffoor 2008; Curtis 2010; Gao, Scherson, and Wells 2014), which has been confirmed in the current study, despite technological innovation in recent years. This highlights the importance of promoting further technological innovation, including energy conservation and wastewater-derived resource recovery options, as well as catchment management strategies that reduce the need for aeration, to reduce water pollution and develop new low-cost treatment solutions. Curtis (2010) presents a comprehensive comparison of alternative strategies and technologies to reduce the need for aeration in WWT. That discussion is expanded below to include newer, state-of-the art technologies and approaches to treat wastewater to high quality standards at lower costs in the following discussion.

A study by the UKWIR (2015), on the cost effectiveness of reducing phosphorus not only in the water sector but also in other sectors, found that measures directed at wastewater treatment works are generally less costly and would achieve a greater improvement in compliance than catchment based measures. Few very innovative nutrient removal technologies with large-scale potential abound. So far, urine separation is one of the few areas of research. However, cultural obstacles are difficult to overcome and, even if they are, urine separation is likely to be seen first in in new-buildings, as it is hard to retrofit into existing wastewater systems. Source separation technologies for wastewater systems are reviewed in depth by Larsen, Udert and Lienert (2013). Water utilities in the UK have also started investing in technologies for advanced pre-treatment which reduces SS/BOD in primary treatment and offloads pressure on ASP systems to reduce energy demand.

Other options include green infrastructure systems, including reed beds, lagoons and wetlands, that are low energy natural systems to pre-treat sewage and runoff at or near the source. Crites, Middlebrooks and Reed (2010) present an in-depth analysis of the design features and performance for multiple green infrastructure options that provide low cost, low energy use WWT. Chouinard *et al.* (2015) carry out a comparative analysis of cold-climate constructed wetlands (CW) in Canada and China. They report on a Canadian study that used CW to treat effluent, which achieved removals of 34% BOD, 52% of ammonia, 90% of phosphorus and 93% of suspended solids. Some newer CW technologies have also been proven to remove emerging organic contaminants such as pharmaceuticals and pesticides, while also removing over 99% of SSs, BOD and NH_4 (Ávila et al. 2015). The cost of building and operating natural treatment systems is usually lower than conventional treatment options, but land requirements are a limitation as well as capacity, thus so far have limited application for large urban areas such as London.

Anaerobic processes, which are widely used in the wastewater sector in warmer regions, could be further integrated into WWT, for example by substituting primary settlement tanks, which would reduce energy consumption, and provide more biogas. Methanogenic systems have shown potential in warmer climates but they perform poorly in colder regions, and are used mostly in small-scale settings, making them uncompetitive (de Mes et al. 2003; Gao, Scherson, and Wells 2014). Decentralization is also gaining traction in the wastewater sector, particularly for new settlements. Chong *et al.* (2011) compared two types of decentralised systems that produce high quality effluent on their energy consumption and GHG emissions, with mixed results. Decentralization may provide benefits for future infrastructure, but it is hard to implement in already established large wastewater systems. Manning, Graham, and Hall (2017) have shown that centralization provides increased process efficiency, and is almost always the better option, although this increased efficiency can be countered by having to pump wastewater through long distances. Oxidation and disinfection include UV light and ozone technologies which are high energy, but with potential for low-cost development. Advanced Oxidation Processes (AOPs) are one such area of research, which involve the generation and use of the hydroxyl radical to oxidize compounds that cannot be oxidized by conventional oxidants. Saharan *et al.* (2014) review AOPs in detail as well as their combinations, making recommendations for the most efficient treatment depending on conditions. They are particularly attractive because solar light can be used in some of the applications (Agulló-Barceló et al. 2013).

Even though the primary function of WWTWs is to remove contaminates from wastewater, they can serve as sources of energy and other materials. Energy recovery from waste is becoming a reality with emerging technologies able to recover significant resources from wastewater (Kretschmer et al. 2016). Gao, Scherson and Wells (2014) discuss the potential of direct energy recovery from nitrogen in WWTWs from different methods such as the CANDO process, which converts ammonia to nitrous oxide gas. Mo and Zhang (2013) systematically review and compare methods for energy generation. Combined heat and power systems have large capital costs, but are appropriate for large WWTWs, and can achieve reductions of up to 26% of electricity consumption (Stillwell, Hoppock, and Webber 2010). All Sludge Treatment centres in the Thames system already use CHP in some form, which is focused particularly at the larger works. Biosolids incineration is another technique that has been applied in WWT and has been reported to reduce 57% of electricity use in some works in the US (Clayton, Stillwell, and Webber 2014). However, incineration does present challenges such as the release of persistent environmental pollutants, quality problems and high capital investments (Mo and Zhang 2013).

On-site effluent hydropower can involve the generation of power from flowing effluent. There are opportunities to develop new or retrofitted generation of renewable energy in the UK's wastewater system (Elías-Maxil et al., 2014). These systems require there to be level differences in the pipes, or between the stream and turbine, as well as enough flow. Other approaches for energy generation include THP (pre-treatment at high pressure/temperature to achieve better digestions and generation), which is being adopted widely in the UK, onsite renewable generation, heat pumps, bioelectrochemical systems, and the use of microalgae. The challenges for energy generation include large capital costs (for example, for combined heat and power systems), lack of reliability and specific requirements for local conditions.

Highly urbanised areas such as London are under multiple pressures, and finding the appropriate methods to treat wastewater to higher quality implies tough decisions and significant trade-offs. It is likely that water utilities will have to continue to invest in end-of-pipe solutions, due to land and other constraints; although work with farmers and other strategies to deal with the sources of contaminants is proving key to reduce the inflow of pollution into WWTWs. The continued decarbonisation of the grid will play an essential part in the water sector's energy and greenhouse gas footprint, as end-of-pipe solutions tend to be energy intensive.

A major limitation to the uptake of new technological approaches, which has been observed in this study, is the lack of technical and scientific information on the applicability, performance, energy costs and sustainability (e.g. emissions) of many emerging options. When the information is available, it is usually not certain enough to make decisions within spending cycles, thus they are not considered. This study has helped to give more concrete and specific areas in which to invest to reduce energy consumption, as well as some potential consequences of not investing, which advances the debate and may reduce uncertainty. There may still be an invigoration of technological innovation in wastewater as carbon prices increase, and water quality standards become more stringent. The water sector's continued involvement in the climate change debate will be key to drive innovation in the area.

Finally, some of the limitations of the present study should be highlighted. The results are limited in that the availability and accuracy of the data was not complete, which increase the likelihood of potential model errors and approximations. Only large WWTWs were used, but more complete studies could assess and compare different sized works. Furthermore, the upscaling of the results may have led to some errors and scale effects. The model considers a set of specific scenarios to illustrate potential future costs. However, possible future scenarios other than the scenarios considered could have been used, and even though several were trialled, different or extreme scenarios could yield alternative results. Further research could aim to quantify these relationships under a larger uncertainty space, as well as under a much larger range of external factors, such as renewable energy uptake or innovative technologies, although new data would be needed to include such aspects.

5.5 Conclusion

This study quantified the relationship between the removal of key pollutants in large wastewater treatment works and the associated energy consumption. It also demonstrated that that the addition of activated sludge processes increases the energy consumption at the works. The analysis was carried out using six major wastewater treatment works in the UK and used to estimate the energy and greenhouse gas emissions of changing effluent standards on wastewater treatment. The results showed that more stringent effluent standards could result in at least doubling of electricity consumption in large WWTWs in the UK, and the addition of between 1.3 and 2.3 $MTCO_2$ per year for the sector. This could have significant financial and regulatory implications for the water sector, and could impact the UK's emissions reduction targets. It was also found that the decarbonisation of the grid will contribute significantly to offsetting the emissions incurred by more stringent effluent standards. However, more coherence is needed between environmental policies to avoid negative trade-offs and meet national emissions reductions without compromising water quality.

6. Multi-objective optimization of energy and greenhouse gas emissions in water pumping and treatment in London

6.1 Introduction

In urban water supply networks, there is little space to make significant operational cost gains. A large part of operating costs is usually derived from energy use, mostly in the form of electricity costs. The aim of this chapter is to demonstrate how multi-objective optimisation can be applied to real-world water supply system problems to support investment decision-making processes in the sector. The main aim is supported by three objectives: (1) to show the potential for reductions in operational energy use through the optimization of existing water supply systems (2), to show the capacity of a multi-objective optimization framework to inform decision-making by evaluating the trade-offs between CAPEX, OPEX and GHG emissions of investment options in a real-world network and, (3) to evaluate how uncertainty influences the choice of investments. This study presents a unique approach to assessing the electricity consumption of water supply through an integrated systems perspective. The study not only includes the distribution network but develops an integrated supply system model that also accounts for water treatment. The model is tested using operational data from a water utility serving London. This approach allows for the evaluation of cost savings by taking the whole system into consideration as well as multiple objectives that a water utility faces in the operation of a water supply system. Furthermore, it not only evaluates trade-offs between investments, operational savings and GHG emissions in an existing network, but it does so within an uncertainty framework.

The chapter shows how a hybrid linear and multi-objective optimization model can provide a way to evaluate the costs of investments within an existing water infrastructure network and deliver operational savings. Whilst, theoretically, significant energy gains can be made within a water supply system, there are practical limitations for utilities in effecting these changes due to competing priorities. The results of the study highlight how the integration of linear and multi-objective optimization provides a useful way to identify key energy bottlenecks in a water supply system, and then evaluate the amount of investment needed to make more significant operational gains at those points in the network. The study also shows that including an analysis of uncertain parameters, namely discount rates and the valuation of greenhouse gases improves the understanding on the most appropriate investment decision. For example, the addition of variable carbon costs showed that there are regions at which the optimal solution for the utility changes. In the cases where greenhouse gas costs are not considered, there may not be enough of a justification to invest in higher energy saving approaches because the solutions are not cost-effective. Methodologies like this one could be used by utilities to support existing decision-making processes by adding a dimension focused on the energy savings of investments.

6.2 Materials and methods

This section presents the methodology for the development of the two-level optimization, which aims to minimize operational energy costs for a given water distribution and treatment network. The methods consist of three main steps. The first step involves the mathematical formulation of the linear optimization problem, and replication of the network to find the optimal daily distribution of water to minimise energy costs, whilst balancing supply and demand. The task of the linear optimization model is to determine the optimal route to supply water that considers the cost at each step, to achieve the maximum net daily savings. In the second step, uncertainty is integrated in the developed network through changes in population, per capita and industrial demand, water available for supply, and energy prices. The third step consists on building the second-level of the optimization, by identifying optimal investment strategies to further improve the operation of the system under uncertainty. To do this, 'bottlenecks' are identified using the upper Lagrange multipliers from the optimal solution in the Linear Programme. A MOEA is run that aims to meet water demand whilst minimizing total expenditure costs for several investments derived from the Lagrange multipliers in the system. The optimization model is run 20,000 times.

The simulations capture significant future uncertainties for the system, which are: population, per capita water demand, industrial water demand, water available for supply, discount rates, energy prices and carbon prices. Several network investment strategies are then evaluated to determine if any of these configuration changes improves the optimal scenario on the system enough to warrant investing in them. Thus, the final target is to identify a strategy with the lowest energy consumption that best meets water demand under uncertainty for a given budget.

6.2.1 Data sources

The asset data used in this chapter was derived from Thames Water datasets presented earlier on in the thesis (Section 2.4), and can be seen in Table 6-1. The water flows used in the model, reservoir and WTWs capacities, network configuration and total energy consumption all derive from empirical data described in Section 2.4. The energy intensity of each asset was obtained by dividing the average daily energy consumption (kWh) by the average daily water flow (m^3) over a period of 60 months for which data was available (see chapter 3 for calculation of energy intensity). Some of the data available was very granular (for example, the capacities, water flows and energy consumption at water treatment works) and some of it was system level (energy consumption of pumps), thus some approximations had to be made (e.g. the pumps all have the same energy intensity, although we know in practice this is not the case). GHG emission costs for proposed capital investments, also known as 'embodied' capital GHG emissions were also obtained from Thames Water. The model formulation, objectives and constraints were discussed with Thames Water modelers to ensure that the approach and model assumptions were sufficiently proximate to the London network to draw some useful conclusions.

Table 6-1: Current asset data derived from various original datasets

	Treatment works	**Capacity (m^3/d)**	**Current Energy Intensity (kWh/m^3)**
GWTWs	GW Sources	286,600	1.02
WTW 1	Chingford WTW	27,300	0.68
WTW 2	Coppermills WTW	525,500	0.23
WTW 3	Hamptom WTW	664,300	0.22
WTW 4	Ashford WTW	682,700	0.12
WTW 5	Kempton WTW	167,200	0.32
WTW 6	Walton WTW	85,900	2.57
WTW 7	Hornsey WTW	30,000	0.15

Source: (Thames Water 2014b)

6.2.2 Mathematical formulation of linear model

The problem addressed in this study can be stated as follows:

Let *G = (T, P)* be a directed network with n nodes and m arcs, where *T* is the set of nodes that represent a source (such as a river) or a storage element (such as a reservoir or WTW) and P is the set of arcs (representing a set of network pipes). Each arc represents a pipe (i,j) $\in P$, *with* a cost c_{ij} that denotes the energy cost of a unit of water in kilowatt hours (kWh) going along the pipe. Researchers have previously approximated the energy consumed by pumps as a linear function of the pumping station water flow, and comparisons with more complex hydraulic models have demonstrated that they are capable of solving real-life pumping problems in a comparable and more computationally efficient manner (Puleo et al. 2014; Giacomello, Kapelan, and Nicolini 2013). Each *P* are also associated with an amount of x_{ij} water flow in meters cubed (m^3) per day. Each element of *T* and *P* are associated with a lower bound l_{ij} and an upper bound u_{ij} of the flow; b_i represents the available amount of supply or demand of water.

$$Minimize\ \mathrm{J} = \sum_{(i,j)\in P} j = c_{ij}x_{ij}, \tag{1}$$

Subject to:

$$\sum_{j:(i,j)\in P} x_{ij} - \sum_{j:(i,k)\in P} x_{jk} = b_i \quad for\ all\ i \in T, \tag{2}$$

Flow capacities in pipelines:

$$l_{ij} \leq x_{ij} \leq u_{ij}, \qquad for\ all\ (i,j) \in P. \tag{3}$$

The first equation is the objective function, where the objective is to minimise the total daily operational energy costs in the network. The second equation is a constraint that assures that the summation of supply and demand around each demand node is zero. Equation three is a constraint imposed to assure no negative water volumes and establish the capacities of each water source, reservoir and treatment works. As similarly approached in other studies (Puleo et al. 2014), the results of the LP aim to inform on the system behaviour assuming that the network hydraulics are completely embedded in the empirical energy consumption relationship and thus in the coefficients c_{ij} of the objective function.

6.2.3 Implementation of multi-objective evolutionary algorithm

The MOEA is implemented to incorporate the LP, in a two-stage optimization fashion. The LP solution (of optimal flow volumes in the distribution network) is provided as an input to the MOEA to optimize each decision option. There is a set of 12 decision options, and they are outlined in Table 6-2. Figure 6-1 illustrates the computational setup.

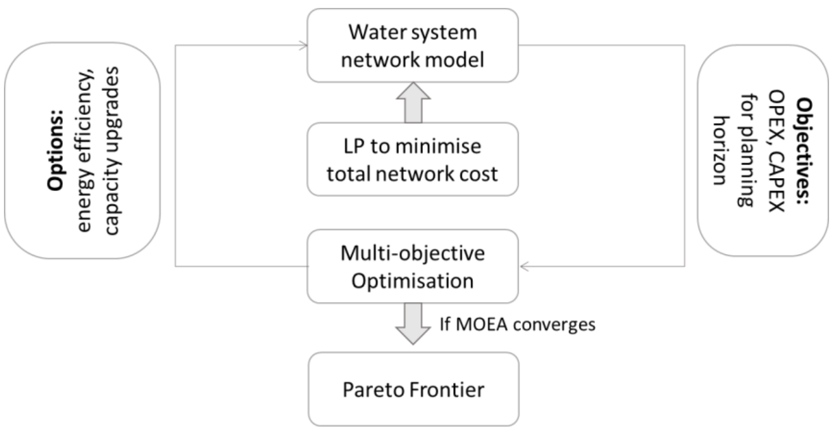

Figure 6-1: Relationship of two-stage LP-MOEA optimization

The optimization is carried out using the multi-objective evolutionary algorithm described in section 4.2.5, evaluating trade-offs between the objectives of capital expenditure and operational expenditure in this chapter.

6.2.3.1 Pareto efficient solution

The final Pareto efficient solution of each Pareto approximation curve was calculated by dividing the change in operational energy costs over the change in capital investment cost, where the maximum E is the Pareto efficient solution for a given multi-objective trade-off:

$$E = MAX\left\{\frac{-\Delta OPEX}{\Delta CAPEX}\right\} \quad (4)$$

This is the point on the Pareto curve at which the capital expenditure provides the largest operational saving.

6.2.4 Application to case study area

To demonstrate the proposed method, the model is applied to the London urban water supply system, located in the Thames River Basin in the South East of England, and operated by Thames Water Utilities. The region is seriously water stressed and climate change is projected to result in a decrease of water availability (Environment Agency 2008b; Burt et al. 2016). The area is also known as the London Water Resource Zone (WRZ), WRZs are described in detail in section 3.2.2. The WRZ is mostly supplied by surface water abstractions from the river Thames via pump storage reservoirs, and by some groundwater abstractions, delivering clean water to approximately 7 million people every day (Thames Water 2015). Water abstractions are subject to limits to maintain environmental flows. A previous study (Borgomeo et al. 2014) identified population growth and abstraction allowance reductions as two of the major uncertain factors posing the greatest pressures on the system.

The London WRZ has the challenge of continuing to supply water to growing populations while at the same time ensuring that its services are affordable for water users. Because it is in a heavily urbanised and densely populated area, the opportunities for operational improvement lie mostly in making the operation of the system more efficient, and in investments at key network points that can reduce the energy consumption of the system.

The study applies the minimum-cost flow network optimization LP to the London water supply area. Flow is minimized based on the energy (kWh), of conveying, treating and delivering clean water to 'demand centres'. A simplified version of the London WRZ is used in this study, covering the main abstraction points and water treatment works (Figure 6-2).

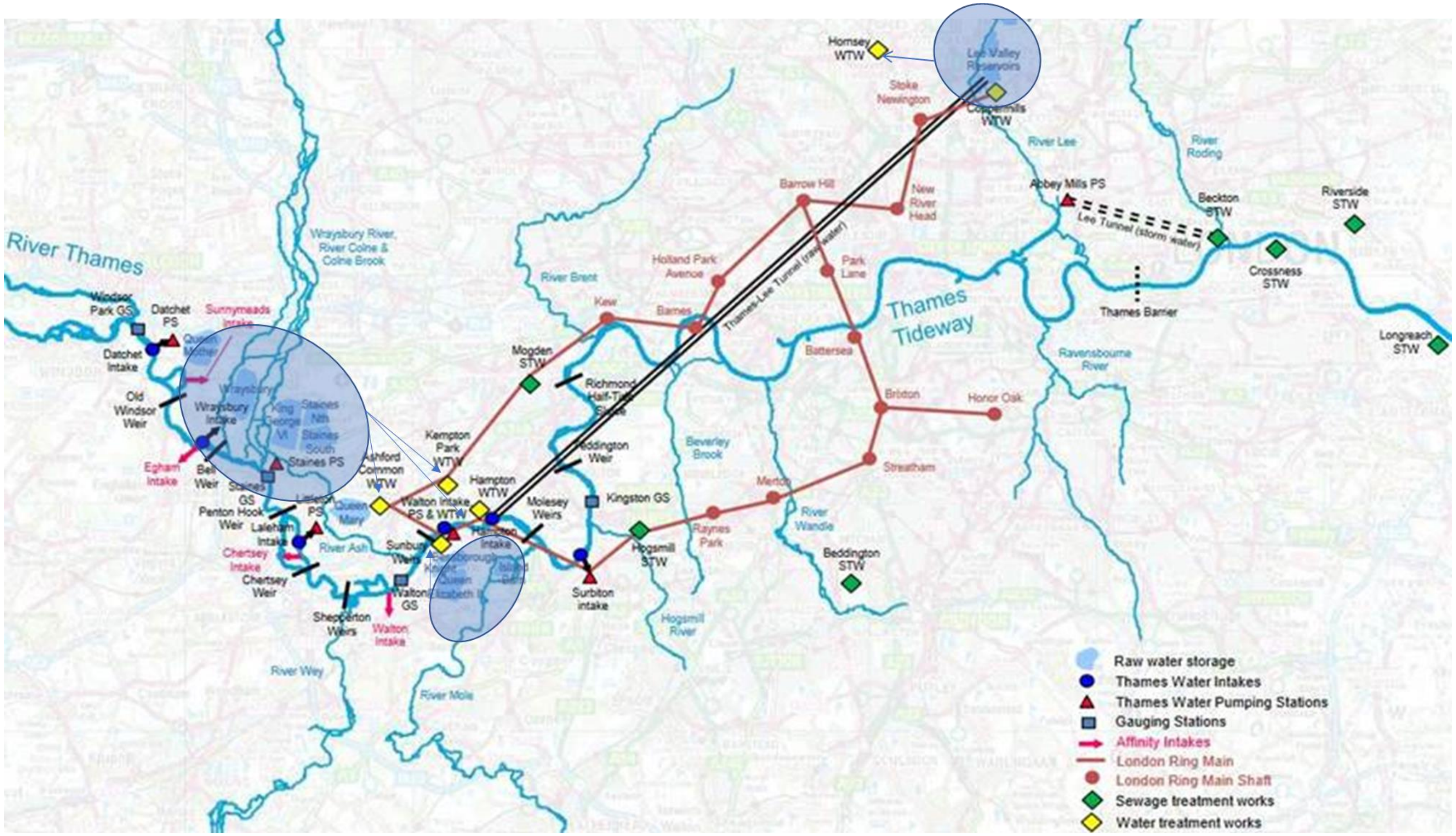

Figure 6-2: The London Water Resource Zone and simulation model (Thames Water 2014b)

Figure 6-2 shows the London WRZ. The ovals over the reservoirs shows how they have been grouped in the model. The yellow diamonds show the surface water treatment works and how they are connected to the reservoirs and the ring main, all of which are represented in the model. A representation of how the model is connected can be found in appendix section 9.4. Evidence from the literature shows that optimisation models benefit from simpler representation of large networks that reduce the number of nodes and thus enable development and implementation of optimization techniques (Mala-Jetmarova, Sultanova, and Savic 2017) The treatment works represent all seven Surface Water Treatment Works in London. The groundwater treatment work (GWTWs) is a conglomerate of all the groundwater treatment works, in which the capacity of all the groundwater treatment works has been summed and an average cost of abstraction used. The groundwater sources have a minimum daily supply requirement of at least 40% of their capacity. This was incorporated after discussions with Thames Water modelling experts to represent the system more accurately, as some London demand has to be met through groundwater sources. The x## numbers represent the assigned names for the optimization for each node and arc of the network. This configuration was used to illustrate the ability of the modelling technique to provide useful investment solutions.

Each reservoir has associated abstraction pumping costs (River to Res connections in network diagram). All treatment works also have transmission pumping costs which are equal for all stations (WTW to demand centre connections). It is assumed that the water pressure in the system is constant and there are no flow variations due to pressure differences. Operational water pressure for the TW network was not available, so the effect of head loss is not included in the model. Because pressure is encompassed within the empirical figures used in the model it is assumed that these variations are captured in the empirical numbers used. If changes in pressure were integrated into a more detailed version the model, more nuanced energy costs for particular sections of the network could be obtained, although these would come at a computational and time cost, but could be useful in more detailed studies looking at pressure gradient improvements for example. Each treatment work has a unique cost per unit of water treated, which is representative of the average cost to treat each unit of water in these treatment works in London. Reservoirs are assumed to have daily capacities matching daily demand unless otherwise stated. Reservoir 4 has a lower capacity than the others (30,000 m^3/d), while the others have virtually unlimited capacity. This was due to lack of data for daily capacities of reservoirs. Discussions with Thames Water experts highlighted that this was not a problem for modelling of daily supply because service reservoirs have capacities far in excess of daily demands. Each treatment work has a capacity which matches the real capacity in these treatment works in London.

6.2.5 Uncertainties

Uncertainty is present in all aspects of water resources management. One source of uncertainty comes from imperfect understanding of socio-economic drivers in water systems, such as water demand, population changes and industrialization. Other uncertainties come from uncertain knowledge on water availability and climatic changes. It is important to understand how these uncertainties influence the optimization process to inform decision-making appropriately.

To test uncertainty in the model, different input parameters are varied using Montecarlo simulations (20,000 runs) to ascertain how changes in different factors would influence the cost of the system. They are:

1. Water demand: change in total water demand, which is a combination of change in per capita demand and change in population.
2. Electricity prices (£/kWh)
3. Carbon prices (£/tCO_2e)
4. Discount rates: the rate at which the value of investment is discounted over time.

In this framework, uncertainty about the input parameters is represented by a set of distributions. The model identifies specific treatment works and pumping nodes, based on the network configuration, where efficiency improvements could provide the largest cost reductions. It then identifies solutions that define the trade-offs between costs and the sensitivity measures.

According to the Thames Water Resources Management Plan (WRMP), the average demand for the London WRZ is approximately 2035 megalitres per day (ML/d). The mean total demand in the optimization is thus 2035 ML/d (which is broken down into a multiplication of the population with the per capita demand plus the industrial and commercial demand for London). Per capita demand is generated from a normal distribution, with a mean of 160 l/p/d, which is the average Thames Region per capita demand, and a standard deviation of 1 l/p/d to capture small variations over the 5-year period under investigation. The 5-year period was deemed as a useful time-frame as it matches the water sector's price review time periods. This is the period over which the regulator, Ofwat, assesses each company's ability to finance its activities (Ofwat 2017; National Audit Office 2015). Gaussian distribution probability distributions are commonly used for Montecarlo simulations of water demand where relatively accurate estimations of demands for a region can be made (Babayan et al. 2005). A right skew Pearson distribution (skew: -0.75, kurtosis: 3.4) is applied to population, as population is expected to increase in the basin. This was done so that the distribution of resulting simulations included a larger number of higher than average demand figures than lower than average, as demand is expected to increase, and thus the uncertainty is rightly skewed. Other population forecast studies have traditionally used rightly skewed distributions to represent the probability that the population will increase (Alho 1997). Demand is calculated as follows:

$$D_T = (P*PC_D) + I_D + C_D \tag{5}$$

Where D_T represents total demand, P represents the population, and PC_D, I_D and C_D represent, per capita demand, industrial demand and commercial demand respectively.

The water available for use (WAFU) is derived from the maximum abstraction allowed for the London WRZ published in the TW WRMP of 2385 ML/d. The availability in the LP is generated from a normal distribution with μ = 2385 ML/d and sd = 10 ML/d. The LP is optimized to meet London's daily demand, and to not exceed the maximum abstraction available for the region. The LP is run for each of the 20,000 simulations.

Electricity prices are derived from forecasted figures for the next 5-year horizon from the UK Government (DECC 2015a). The electricity price is thus generated from a normal distribution with μ = 0.125 £/kWh and *sd* = 0.01 £/kWh. It is important to note that electricity prices are not just uncertain, but also variable on short timescales, and that is why an uncertainty analysis around electricity price changes is carried out.

6.2.5.1 Greenhouse gas emissions

The operational greenhouse gases are calculated by multiplying the daily kWh consumed by a unit rate (emissions factor) to generate a tCO_2e from a kWh. The emissions factor is varied in the Montecarlo simulations to assess the impact of a decarbonising grid, with a mean of 0.212 $kgCO_2e$/kwh and a standard deviation of 0.05, to incorporate higher end emissions factors closer to today's rates (around 0.4) and projected changes of down to 0.1. Capital investment embodied greenhouse gases are calculated from Thames Water's 2017 driven rates for embodied carbon of proposed capital investment options in tCO_2e/£, provided by the utility. Carbon prices were also used to calculate the monetary cost of greenhouse gas emissions. These were derived from the UK government's carbon price values used for UK public policy appraisal (DECC 2015b). They publish three scenarios low, central and high, with approximate values of 4, 21 and 46 £/tCO_2e. The starting multi-objective optimization is carried out with the central value.

6.2.6 Investment strategies

For the εMOEA optimization, several investment strategies are tested that help to evaluate the operational energy savings that can be achieved from given investments. A Pareto approximation cost curve is derived that gives an indication of how much capital investment would be needed to warrant specific operational gains. The water utility can then use this to evaluate the costs of different technologies or capacity expansions versus the potential savings that such technologies may provide, for a given budget.

Opportunities for improving the performance of the system were identified with the outputs from the LP, using the Lagrange multipliers. The optimal LP was used as a basis to identify strategic options for CAPEX investment solutions. The Lagrange multipliers from the LP show how much the optimal cost solution value would change if a constraint of cost or capacity is relaxed. They show the nodes of the network where if the constrains are relaxed, the solution can be further improved. This is a rigorous methodological approach to improving the system, which has traditionally been based just on expert knowledge. The investment options presented in this paper were first identified with the Lagrange multipliers, and then discussed with the utility experts to determine the feasibility of the options.

Table 6-2 shows the type, location, capacity and further details of the investment options included in the model, alongside their CAPEX and OPEX (represented by energy costs). The capital costs for proposed investments that included pumping were derived from Thames Water's in-house process model for pumping stations. The final capital costs in the model thus depend on the ML/d required to be pumped, for which a cost is produced. They also depend on the type of pump, as abstraction pumps (e.g. river to reservoir) have a different cost curve to pressurized distribution pumps. The final capital cost depends on the type of pumping station, the power required for the pump, the head and the ML/day that would be pumped through the proposed station, thus the costs are variable.

Table 6-2: Short-term investment strategies derived from optimal LP model

	Type of investment	***Location of investment in network***	***Capacity (m^3/day)***	***Investment details***	***CAPEX (£000s)***	***OPEX*** (kWh/m^3)
1	Capacity upgrade	Chingford WTW	27,300	Expand up to 32,760 m^3/d	278*	0.68
2	Energy Efficiency improvement	Walton WTW	85,900	Use new technology to increase efficiency. Reliability factor associated to the technology included	160**	2.57 – improved up to 1.7
3	Capacity upgrade	Hornsey Reservoir and WTW	30,000	Increase the capacity of reservoir and WTW up to 33,000 m^3/day	303*	0.15
4	Capacity upgrade	Ashford WTW	682,700	Expand up to 750,970 m^3/day	4723*	0.12
5	Energy Efficiency improvement	Groundwater pumps	286,600	Groundwater pump replacement results in a 2-10% gain in the energy intensity of groundwater pumping[b]; there are 31 stations.	Thames Water process model[a]	1.02 – improved by up to 10%
6-12	Energy Efficiency improvement	Main distribution pumps in system	NA	Improve pumping energy use by 2%: VSDs increasing the efficiency of the pumps in the water distribution system implemented, improving the energy intensity from 0.117 kWh/m^3 to 0.116 kWh/m^3	Thames Water Process model[a]	0.167 – 0.105 improved by up to 10%

*estimated from plant capacity construction cost curve for existing plants; originally established by Hinomoto (1977)

**estimated from the capital cost of installing an efficient UV technology in a medium sized WT plant (National Research Council 1999)

a estimated from VSD pump costs reported by Ferreira et al. (2011)

b from Nogueira Vilanova & Perrella Balestieri (2014).

These investment options are by no means exhaustive, and some may not be feasible due to other external constraints, such as land limitations; but they illustrate the capacity of this model set-up to provide an indication of where costs can be saved within a water distribution and treatment network, and provide a cost trade-off for each investment option. The cost of the investments is calculated for a five-year return on investment period, following current water industry regulation, and discounted at the industry's used rate of 3.5%, a rate which is later treated as uncertain.

6.3 Results

6.3.1 Linear Programme

The LP results show that optimizing the system based on energy cost provides an approximate 18% daily saving in energy consumption of the water distribution and treatment system, from an average daily total energy consumption of 1.15 million kWh to 939,000 kwh per day. It also provides an average optimal annual cost in pounds of approximately £42.8 million per year to run the network. Thames Water currently spends approximately £50 million per year to operate the water network in London, thus using optimising techniques for the network could provide significant annual savings. TW reports to Ofwat show that their annual average operating expenditure for water delivery for their whole region is £327 million a year (Ofwat 2010b). This includes other areas outside of London, and contains other costs such as staff costs, maintenance costs, insurance, vehicles and other miscellaneous costs.

Discussions with experts within the case study utility to validate and discuss the model output place this result within the context of the daily operations of a water utility. Such savings are currently not being achieved in practice because water utilities have competing priorities to fulfil. The first is security of supply. Even though some sources of water within the network are very costly, for example, groundwater supply, there are sections of the network that require water from these sources to meet demand, and thus they need to be used daily at a high cost. Some of these are captured in the model, such as groundwater source requirements, but not all. The second priority is ensuring high water quality. Due to the variable nature of water quality, for example, the emergence of algal blooms seasonally, some more efficient parts of the network sometimes need to be turned off to avoid contamination, thus requiring more costly areas of the network to be run. Such modifications occur on a regular basis, requiring expensive resources to be turned on often. The third is the avoidance of leakage. If an efficient section of the network suffers from increased leakage, for example, from a burst pipe, supply is drawn away from that area and more costly water supply options may be used that would not be used otherwise, to avoid water losses. The reduction in energy consumption is thus currently the fourth priority for the case study utility, and most likely for the whole sector. These priorities added together mean that, in practice, it is difficult for utilities to make large energy gains.

However, discussions with experts from the utility did bring out that there are opportunities for more coordination between priorities, to improve the understanding of the connections between operating goals and energy costs, and benefit from potential savings. Studies such as this one can support such coordination and contribute to cohesion between objectives by showcasing methodological approaches that could be used in conjunction with existing processes for operating networks.

Table 6-3 presents a comparison between the volumes of water treated in the existing system (and associated empirical operational energy costs provided by Thames Water), with the optimized results for the water treated (in m^3) in each treatment work and associated energy costs (in kWh) without any additional investments. The figures in this table are lower than the overall system results above because they focus only on the water treatment works, and the overall result also includes pumping figures.

Table 6-3: Comparison of LP optimization results for the main WTWs with operational figures for validation

	Treatment works	Current average water provision (m^3/d)	Current average daily energy use (kWh/d)	Model average water provision (m^3/d)	Model average daily energy use (kWh/d)
GWTWs	GW Sources	200,800	154,104	114,000	116,394
WTW 1	Chingford WTW	7,698	7,885	0	0
WTW 2	Coppermills WTW	458,372	105,056	523,606	120,429
WTW 3	Hamptom WTW	520,377	106,134	664,300	146,146
WTW 4	Ashford WTW	617,381	75,381	682,700	81,924
WTW 5	Kempton WTW	138,688	44,224	21,176	6,776
WTW 6	Walton WTW	26,780	55,609	0	0
WTW 7	Hornsey WTW	30,000	4,404	30,000	4,500
Total	-	**2,000,096**	**552,798**	**2,035,782**	**476,170**

As can be seen, even though the actual treatment works provide less water, on average, than the modelled results (around 35,000 m^3/day, most likely due to daily variations in water supplied), the total energy consumption is significantly lower for the modelled results (476,170 kWh/day) than the current system (552,798 kWh/day). There is variation in the volume of water being treated at specific works and the energy costs due to the system being optimised to save energy as a whole.

6.3.2 Multi-objective evolutionary algorithm results

Figure 6-3 shows the εMOEA trade-off between capital investment costs and operational energy costs. Each point in the figure represents a unique combination of investments. The solution A lying on the x axis is the LP optimal result. The LP resulted in an optimal average 5-year discounted operating cost of approximately £126.2 million pounds. This is the single optimal solution for minimizing operational energy consumption in the network without additional investment, and for a set of specific starting condition parameters which are later treated as uncertain (see appendix section 9.5). The solution C is the Pareto efficient solution in the Pareto-approximation curve, as defined in section 6.2.3.1. It is the point at which the relative operational energy savings are the best in relation to the capital investment. The εMOEA results show the trade-off between the capital costs of different combinations of investment strategies and the operational 5-year discounted costs for each of these optimal combinations. The εMOEA, even though computationally time-consuming, allows for a visualization of a Pareto-approximation frontier and trade-off between multiple objectives, showing how with more investment operational savings can be made. This permits a more in-depth evaluation of options to the water utility based on available investment budgets. Furthermore, it allows the water utility to calculate the recoupment period for each investment combination.

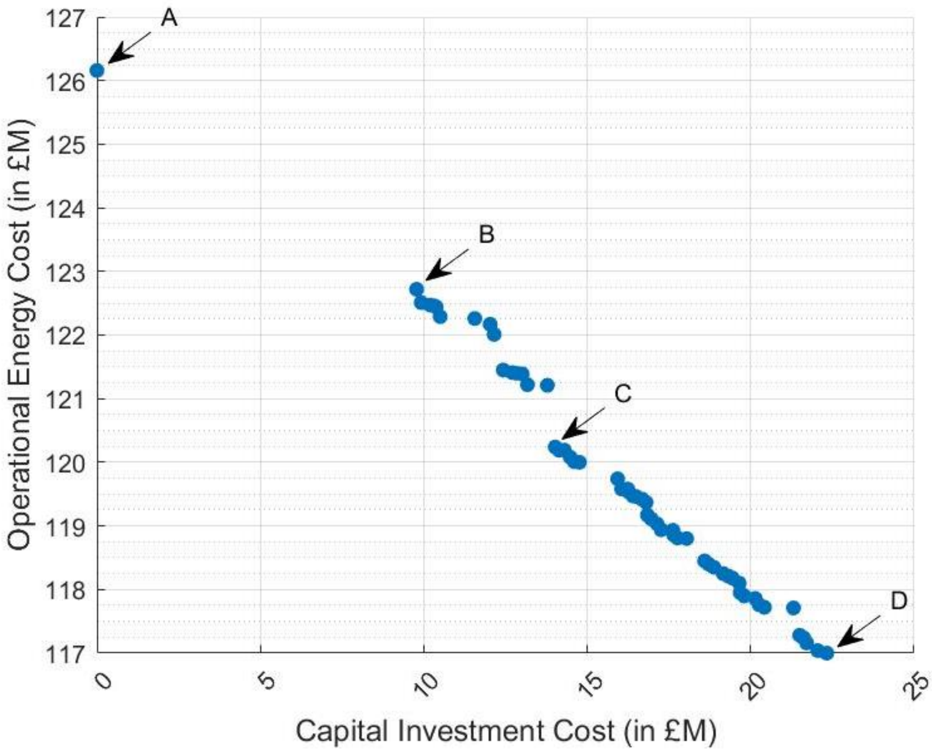

Figure 6-3: Multi-objective trade-off between CAPEX and OPEX costs

The Pareto curve in Figure 6-3 appears linear, but is in fact many small Pareto curves made up of a combination of increasing capital investments which happen to assimilate a linear increment when seen together. Figure 6-4 shows a close-up of the location of solutions B, C and D in order to visualize the small Pareto curves at those locations, the Pareto efficient solutions can be seen in a different colour.

It may appear that operational cost savings are not large enough when compared to capital investment. However, the figures shown only show the savings over a 5-year period, but the life cycle of investments are in the range of 30-40 years, or even more. Thus, operational savings of about ~£5 million in a five-year period for a £~14 million pound investment, as seen in Figure 6-3

Solutions A and C can provide a large saving over the life-time period of the asset. In this case, the evaluation is 5-year because of the budget cycles in the UK, as outlined above, but water utilities also plan in longer-term frameworks.

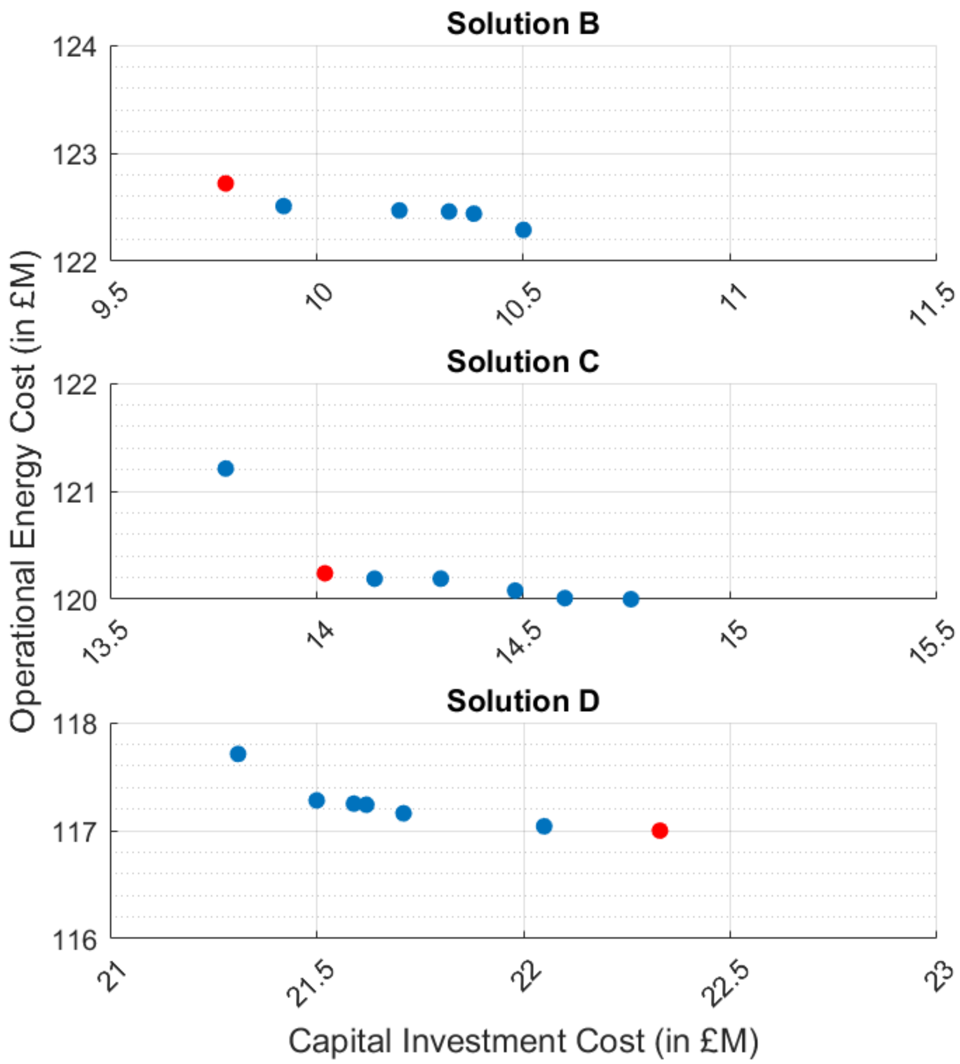

Figure 6-4: Slices of Figure 6-3 showing the Pareto curves of specific solutions

Solutions B and D are the lowest and highest combination of capital investment respectively and are chosen with C (the Pareto efficient solution) to explain in detail in Table 6-4. Solution A has no capital investments. There is a gap between solution A and B because the capital investment at solution B is the minimum amount needed to reach an optimal combination of capital investment and operational energy costs. Table 6-4 also shows Pareto efficient solutions as defined in section 6.2.3.1.

Table 6-4: Optimal Solutions showing Pareto efficient solutions (E)

Solution	Capital Investment (million £)	5-year discounted Operational Energy (million £)	Investment Solution details
A	0	126.20	NA
B	9.78	122.72	-Ashford expansion -GW pumping -5/12 distr. pumps
C*(E)*	14.02	120.24	-Ashford expansion -GW pumping -6/12 distr. pumps
D	22.33	117	-Ashford expansion -Walton efficiency -GW pumping -12/12 distr. pumps
Change in discount factor			
E*(E)*	5.97	99.06	-8/12 distr. pumps
F*(E)*	9.41	151.01	-GW pumping -7/12 distr. pumps
Inclusion of GHG emissions			
G*(E)*	14.46	124.85	-Ashford expansion -8/12 distr. pumps
Change in carbon price			
H*(E)*	11.45	121.67	-9/12 distr. pumps
I*(E)*	10.5	131.27	-8/12 distr. pumps

All the solutions in in the Pareto approximation curve include using groundwater pumping in the investment solution. This is because the model has a constraint where a minimum amount of water needs to be extracted from groundwater systems, as occurs in the actual system, which is a more expensive source than some surface water treatment works. All the solutions on the Pareto-approximation curve also involve investment in capacity expansion at Ashford WTW. Ashford is already a large and efficient WTW, so re-routing more water through this location improves the energy consumption of the system significantly.

Water utility decision-makers can use this trade-off and options to evaluate whether they would be cost-effective, for example within 5-year or 10-year investments cycle. The above optimal solution C would save £5.9 million within a 5-year investment cycle. Undoubtedly, this trade-off evaluation does not consider additional costs such as staff costs, land costs, insurance costs, capital maintenance costs and other externalities. But with more complete datasets available in-house to the utilities, such tools could provide very useful information to improve performance of water networks at key nodes.

6.3.2.1 Discount rate

To test the sensitivity of the solution to changes in the discount rate. Two additional Pareto-approximation curves were generated with different discount rates (2% and 5%) in addition to the industry standard of 3.5%. Figure 6-5 shows the original trade-off curve at 3.5% and two additional Pareto-approximation curves, with their corresponding Pareto efficient solutions E and F. As can be seen, a change in the discount rate affects the costs in the trade-off curves and the optimal solution. Higher discount rates reduce the operational cost more and lower discount factors mean higher operational costs. The capital investments are unchanged as they are Net Present Value figures.

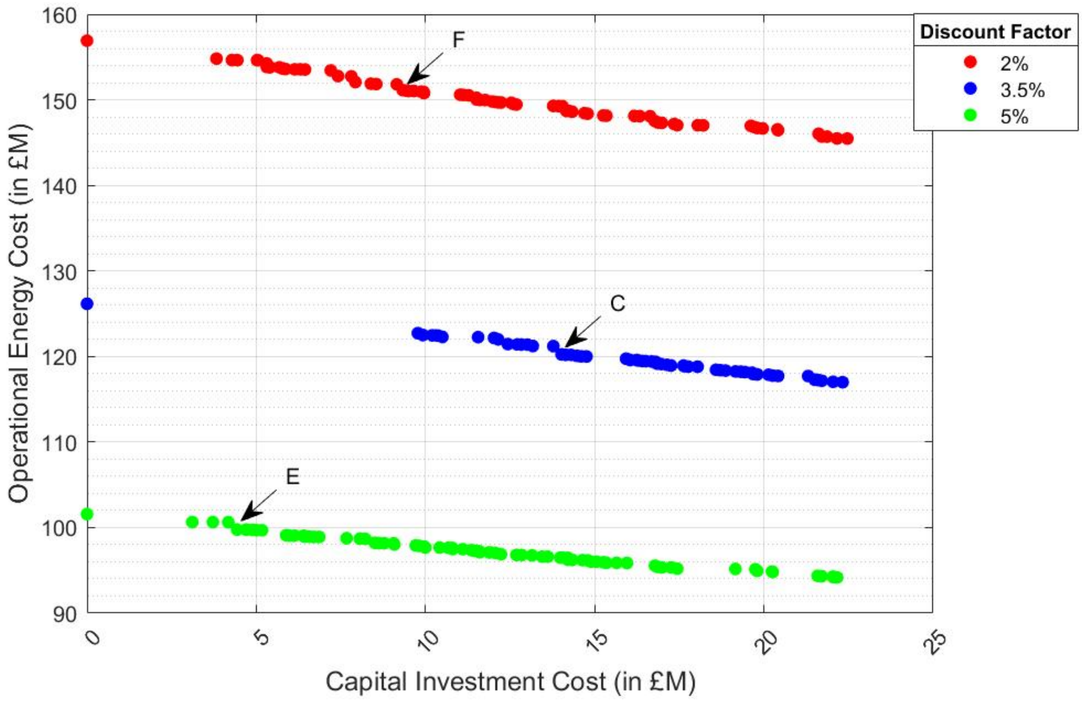

Figure 6-5: Multi-objective trade-off between CAPEX and OPEX costs with different discount rates

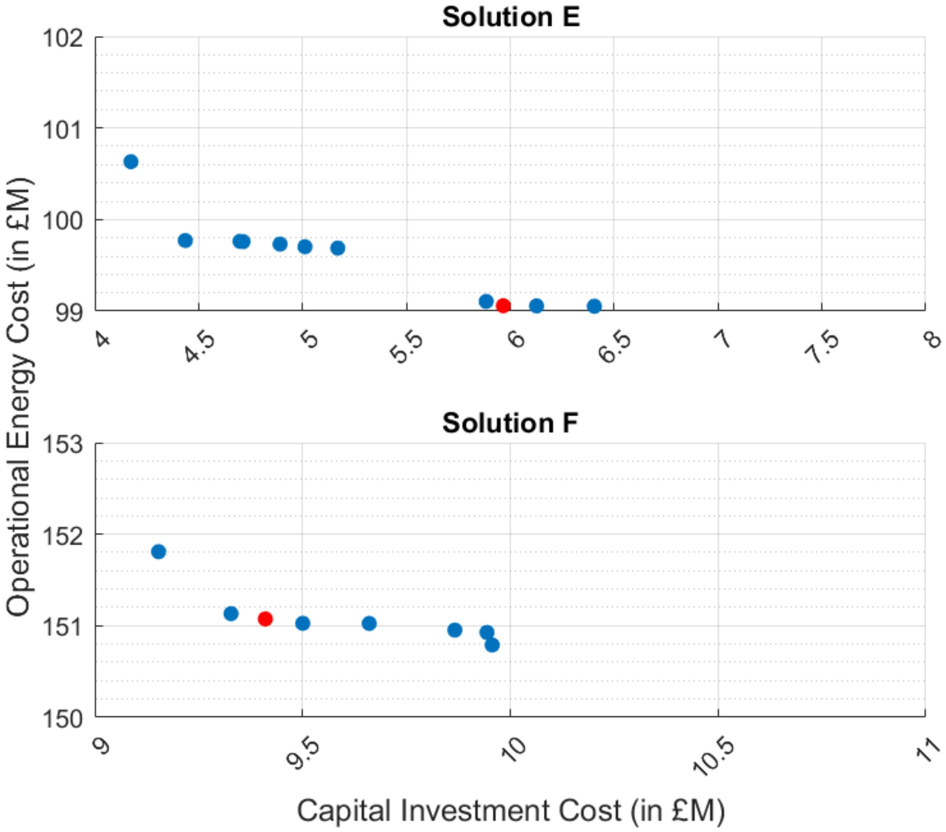

Figure 6-6: Slices of Figure 6-5 showing the Pareto curves of specific solutions

Solution E does not include the groundwater efficiency improvement as previous solutions have done, including Pareto efficient solutions C and F, which is why the capital investment is comparatively smaller (Table 6-4). This is probably because the investment cost of groundwater efficiency improvements is higher than the discounted operational cost of the pumps.

It is interesting to point out that the 'recouping' percentage – how much of the capital investment is made back over the 5-year period- is quite different for the lower discount factor over the two other solutions. For optimal solution C it is 41%, E is 42% and F has a saving of 62% of the investment. This is most likely to do with the lower discount factor allowing for a larger saving over the 5-year period.

6.3.2.2 Greenhouse gas emissions

The analysis is continued with the central discount factor (3.5%) to evaluate the difference in the optimal solution and multi-objective optimization results when the capital and operational costs of greenhouse gas emissions are considered in the analysis.

Figure 6-7 shows the original 3.5% trade-off curve between capital investments and operational energy costs (in blue) and a trade-off curve that includes capital investments costs plus the embodied capital investment costs from greenhouse gas emissions on the y axis, and operational energy costs plus operational greenhouse gas emission costs on the x axis (in yellow). The two curves show the difference between just considering direct capital and operational energy costs and adding the costs of greenhouse gases emitted to the calculations. It is important to note that there are other costs involved in the building, maintaining and operating of water supply options, but this analysis aimed to investigate how the addition of greenhouse gas emissions may alter optimal solutions, particularly when considering carbon price changes. Thus, the graph includes direct capital and operational energy costs plus the greenhouse gas emission costs involved in the proposed capex and the greenhouse gas emissions in the operation of the network. No slices of this figure are made because Solution C is presented in Figure 6-4 and Solution G in 6-9.

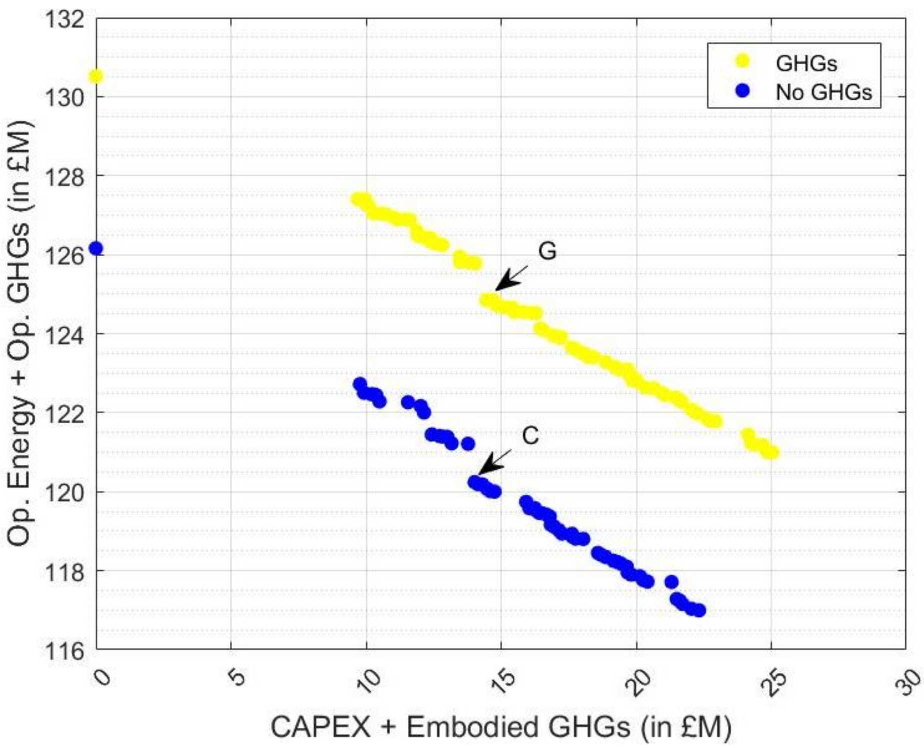

Figure 6-7: Multi-objective trade-off between CAPEX and OPEX, and CAPEX and OPEX with GHGs

Solution G is the Pareto efficient solution when greenhouse gas emissions are considered in the trade-off (Table 6-4). The investment in solution G is similar to solution C in that it also includes an expansion at Ashford WTW, but it does not include an improvement in the energy efficiency of groundwater treatment.

This is probably due to the high embodied capital costs of improving so many pumps. It instead includes an upgrade in 8 out of the 12 large water distribution pumps in the system, instead of the 6 in the original solution, denoting how an inclusion of greenhouse gas emissions changes the best investment choice. The embedded greenhouse gas costs in the capital investment are small compared to those in the energy costs, but could become significant if the carbon intensity of electricity is reduced to close to zero.

6.3.2.3 Carbon Price

The Pareto-approximation curve including greenhouse gas emissions costs was subjected to a sensitivity analysis to evaluate the influence of a change in carbon prices. Figure 6-8 shows three curves, each representing a multi-objective optimization trade-off between capital costs and embodied capital greenhouse gas emissions on the Y axis and operational energy and greenhouse gas emissions costs on the X axis. The central curve is the same as the greenhouse gas emissions curve in the previous figure and has a carbon priced of 21 £/tCO2e. The other two curves represent the trade-offs with a carbon price of 4 £/tCO2e and 46 £/tCO2e and the details of the Pareto efficient solutions H and I can be seen above in Table 6-4.

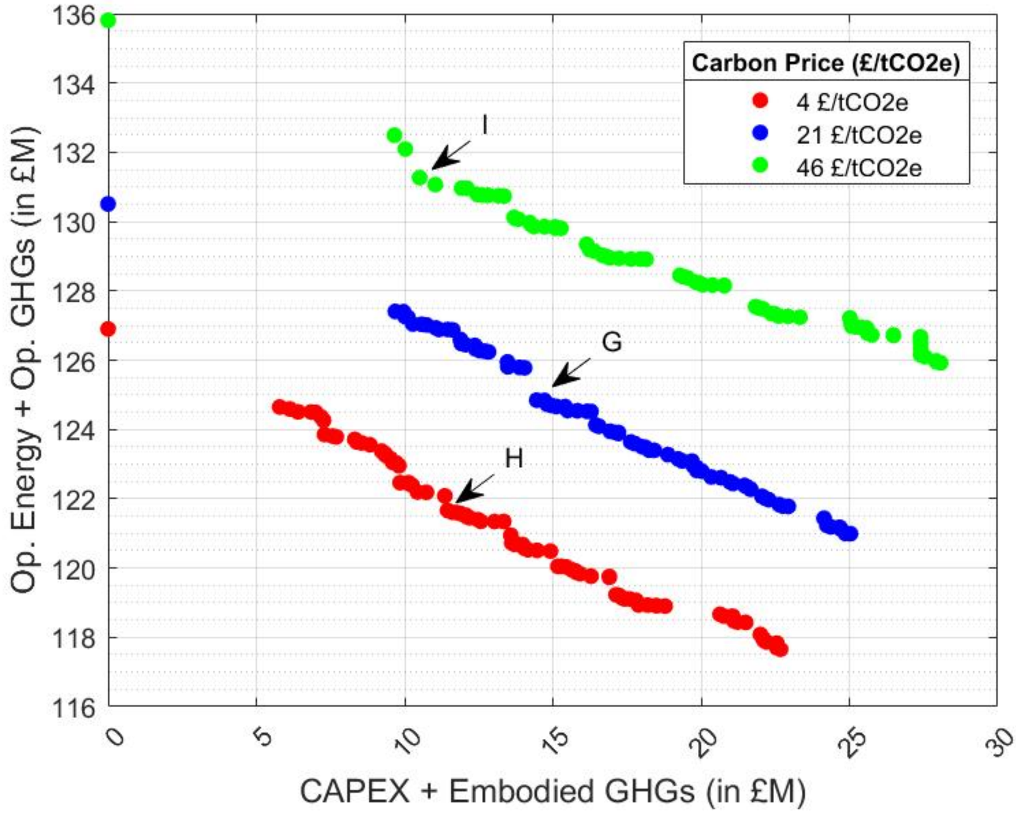

Figure 6-8: Comparison of CAPEX and embodied capital GHGs with operational energy and GHG costs

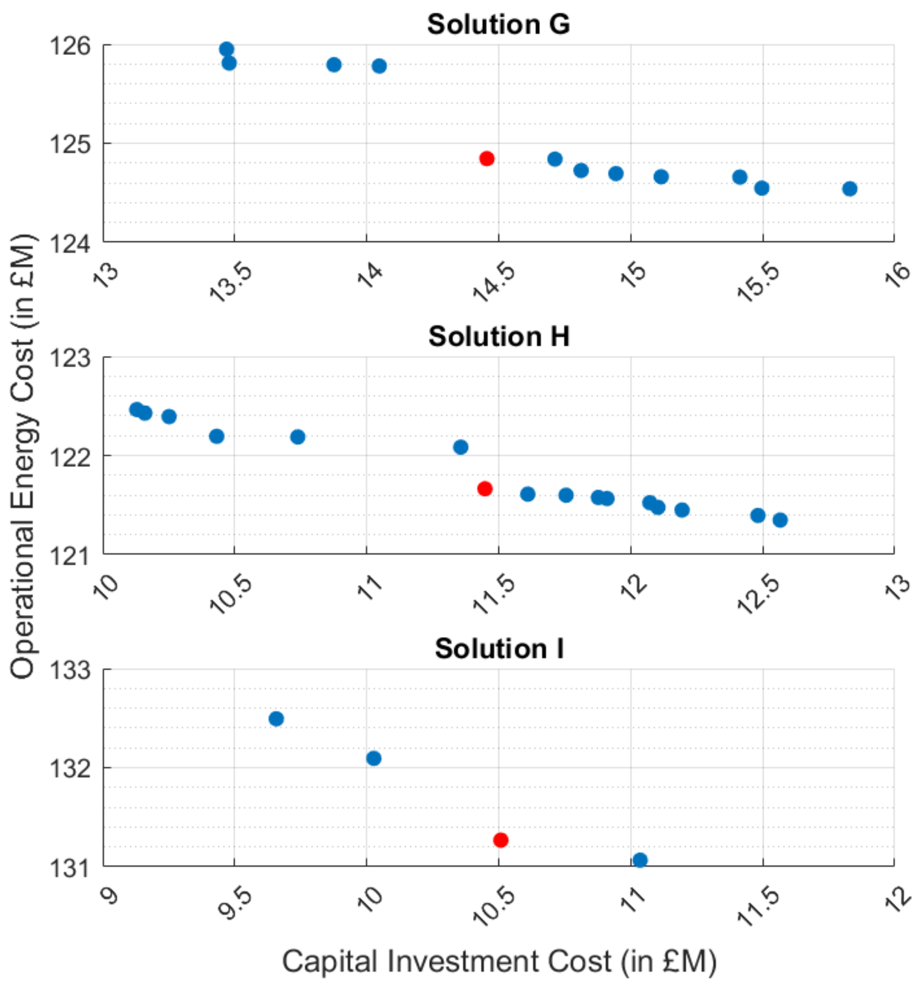

Figure 6-9: Slices of Figure 6-8 showing the Pareto curves of specific solutions

6.3.3 Sensitivity of optimal solution

There are two additional sources of exogenous uncertainty in the model that may influence the optimal solution. As mentioned previously, electricity prices are not just uncertain, but also variable on short timescales, so an uncertainty analysis to the variability of energy prices can provide a more accurate representation of how costs in the system may vary in the short term. Figure 6-10 shows how optimal solution G (which includes the costs of greenhouse gases) would vary with changes in the additional two sources of uncertainty: change in water demand (made up of population change and per capita demand) on the x axis and change in energy price on the y axis. Each dot on the figure represents one scenario out of the 20,000 runs. The figure is coloured by the total 5-year discounted cost in pounds to see how the sources of uncertainty affect the change in cost.

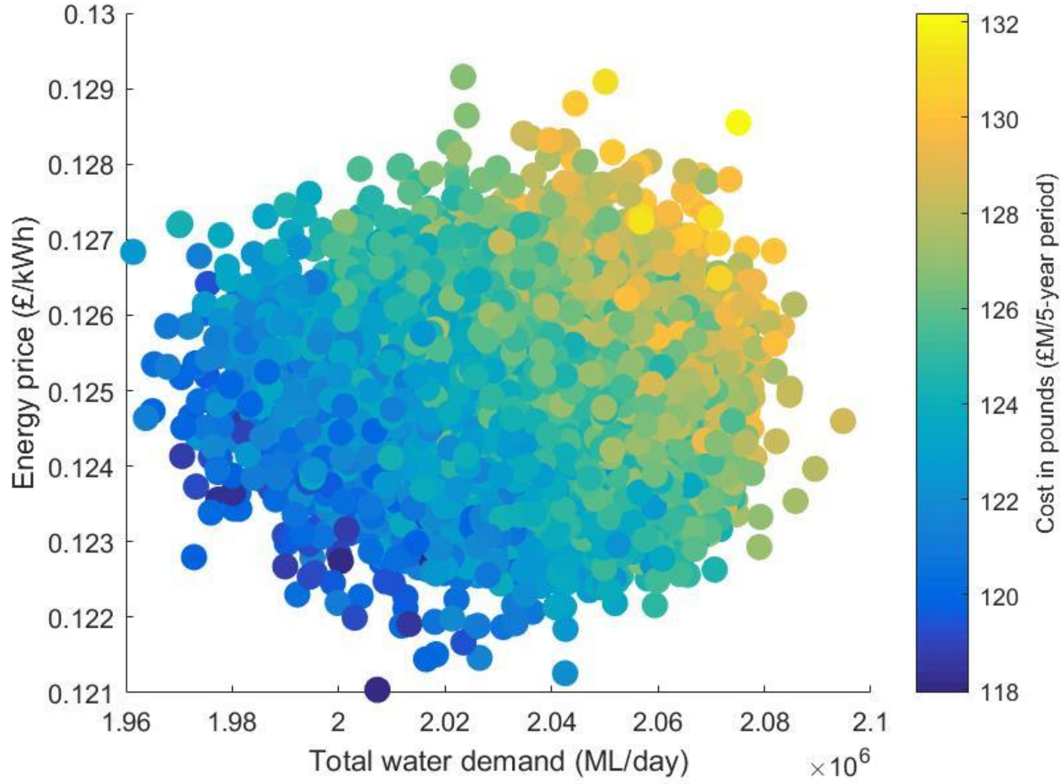

Figure 6-10 Cost in pounds change with total water demand change and energy price change

The figure shows how increases in demand raise the average operational energy costs in pounds, as does an increase in energy price. The results suggest that both small changes in water demand and energy price could increase operational energy costs by between 2 and 5%.

6.4 Discussion

Major cities around the world have limited options for extensive water supply re-design in order to reduce their energy costs, and at best can only consider changes to operations and a few infrastructure projects to affect energy use and GHG in water supply system. Within the LP solution, savings of up to 18% of daily energy consumption were achieved by optimizing the system to minimize operational energy use when transporting and treating water through the network. Other studies attempting the optimization of water networks by minimizing operational results have achieved results in a similar range of 5-25% in energy cost savings (Cherchi et al. 2015), supporting our finding that optimization for the operation of water networks can be a useful tool to support energy management decisions in water utilities. As mentioned above however, discussions with the utility showed that these tools are useful only to the extent that they fit in with the other key priorities within utilities. Decisions take place within a wider set of requirements, particularly provision of high quality water.

This study has methodological and two case specific contributions. Methodologically, the study showed how a hybrid linear and multi-objective optimization model can help to evaluate trade-offs between operational energy costs and capital investments within a water supply network. Visualizing the generated sets of Pareto-approximate optimal solutions helped to evaluate how different uncertainties could affect projected costs and recoupment of investments within a network, particularly discount rates and carbon prices.

The simplified system model is computationally amenable, yet yields result that can inform planning for utilities and local water agencies. The approach is applied for the city of London with actual operational data, which is a key differentiating feature of this work where most studies have used simple theoretical models or theoretical data.

Within water utilities, a breadth of elements is considered when making decisions. This approach widens the number of dimensions that can be considered in decision-making processes to energy and greenhouse gas costs, and suggests a way in which such methods can be used in conjunction with traditional decision-making processes to make the decisions more sustainable and cost-effective.

Furthermore, the model quantitatively identified key bottlenecks in the network through the LP Lagrange multipliers, allowing it to rigorously identify parts in the network that would provide the biggest operational savings. This approach could be used within water utilities to broaden the options considered in water supply planning and provide alternatives that can also reduce their operating costs. A follow-up study from this one could develop a more detailed network representation with a water utility, and carry out a stakeholder consultation process to evaluate whether any feasible water supply solutions could be developed at key energy reduction spots to both increase water supply and improve the energy efficiency of the system at the same time.

The key case specific results are two-fold. The first is that small changes in the regulatory and planning framework, such as discount rates or carbon prices can have important implications for the cost of investment within water supply networks, and are thus important elements to consider when evaluating the costs of possible solutions. GHG prices have an impact on the cost of water system operations, and there are regions of change at which the optimal solution for the utility changes. Under cases where additional external costs such as GHG prices are not considered, there may not be enough of a justification to invest in higher energy saving approaches because the solutions are not cost-effective. When wider costs are included, a more realistic recoupment of investment can be evaluated and the case for higher investment made.

Secondly, changes in water demand, including per capita use and population can have an important effect on the operational energy costs of water supply systems. Conservation measures and behavioural change are key for reducing water demand and associated energy implications. The results of this study quantified this impact for the city of London, showing that a reduction in 3% in water demand can result in a 2-5% saving in operational energy costs, including GHG emissions costs.

6.4.1 Benefits and limitations of approach

The study results should be taken in the context of the modelling exercise and its limitations. First, the model is a simplified version of the London water supply system, which is in effect made up of a complex network of pumps and water sources, including the London ring main which has the capacity to pump in both directions, something not captured in this model, which makes the current model conservative because fewer options are available for energy efficiency improvement in pumping through the network. The computational time for each multi-objective optimization Pareto curve took between 12-18 hours of running time for between 10,000 to 20,000 iterations. It was performed using a i5 Intel Core machine with a 3.4 GHz processor on a 64-bit operating system. More complex system representation and number of uncertainties would increase the computational time required for running the model and may deem it too slow to be usable, although it would yield more realistic solutions to the energy problem, and could include other competing priorities facing water utilities. An assessment of the time investment available to utilities and other users which could benefit from these approaches, versus the detail required for the approach to be useful to decision-making processes would be an interesting avenue to explore.

Another limitation of the model includes the large number of uncertainties that affect such modelling approaches. This not only includes exogenous uncertainties affecting the actual water supply system, of which there are more than presented in the model, but also uncertainties within the model parameters themselves. The most energy intensive treatment sources result in little or no water being treated at these sites at all, and most others being used to capacity. In actual water management, it is difficult to selectively use a subset of WTWs at full capacity, and other treatment sources are needed. Furthermore, there are most likely local restrictions to water abstraction at the sites of each of these treatment works. That is, a WTW in the network may have a capacity of 682,700 m^3, but the water utility may be permitted to only abstract, for example, a maximum of 650,000 m^3 at that location to maintain environmental flows or to dilute other inputs coming into the river. Thus, even though the exercise provides a useful insight into how water can be supplied by putting a higher emphasis on reducing energy costs (and associated monetary costs), there are additional practical limitations that this exercise does not capture, mostly due to lack of data but also due to added complexity. Further details could be added to the model to make it more realistic if data becomes available.

The approach presented in this study only considers operational energy consumption and direct costs from greenhouse gas emissions. In practice, operational energy costs are made up of additional elements, including personnel costs and other maintenance and operating costs, which were not included in the model due to lack of data and complexity. Further versions of this model could add a cost factor for other expenditures found within operational costs to make the results more realistic.

As mentioned previously, the investment strategies presented in the model, although derived from a rigorous methodological approach are hypothetical solutions and many may not be realisable within the existing network, due to land restrictions or other requirements. The model does demonstrate however that there is a use for such approaches to find bottlenecks where large gains can be made within systems, but the process would benefit from a consultation with relevant stakeholders to asses which options could be realistic options and should be used within such a modelling framework.

6.5 Conclusions

This study has presented a novel methodological approach to assess the energy and greenhouse gas emissions costs of short-term investment decisions within a water supply infrastructure network by incorporating linear optimization with multi-objective optimization. The study has considered water treatment and water distribution in an integrated system model. The study used an illustration of a real-world urban water supply system, with operational data, and included the whole water supply network, thus approaching the problem from a 'systems' perspective. The study also used the Lagrange multipliers generated from the linear programme to systematically and quantitatively identify bottleneck areas in the network which were not allowing further energy efficiency gains. These were then evaluated as ‘investment strategies’ with associated capital costs derived from discussions with experts from within the water utility and the literature. The conclusions of the study show that linear optimization can provide important operational energy savings in the daily operation of water supply systems, although these are subject to limitations due to competing priorities within utilities. The application of the multi-objective optimization showed how differences in discount rates and carbon prices can affect the outcome of investment decisions, even as far as to potentially change the investments made within a network. Particularly with greenhouse gases, there is region of change at which the optimal solution for the utility changed. When the GHG costs were considered, the best solution changed. Furthermore, under cases where additional external costs such as GHG prices are not considered, there may not be enough of a justification to invest in higher energy saving approaches because the solutions are not cost-effective. The study demonstrated how there is space for such methodological approaches to be used in the sector to support existing decision-making processes and contribute to the identification and selection of least-cost investment portfolios for water supply.

7. Conclusion Chapter

7.1 Thesis conclusions

Two of the greatest challenges facing society are the provision of clean water and energy. Energy and water are inextricably connected and cannot be managed independently. Despite this, the water and energy sectors have traditionally developed and been managed without overlap. This thesis demonstrates the importance of understanding water and energy interdependencies in detail, through a focus on water-related energy. The main aim was to *evaluate the use of energy in water infrastructure systems and introduce a quantitative approach to understanding current and future relationships*. This aim has been addressed through three main objectives outlined in Section 1.2, and supported by four main chapters covering specific characteristics of the water-energy connection. The objectives were to:

1. Identify, map and quantify the energy consumption patterns and energy intensity of water and wastewater infrastructure systems.
2. Develop a methodological approach to incorporate detailed energy costs into water and wastewater resource planning decisions.
3. Evaluate energy implications of alternative management strategies and technological investments to inform policy development and decision-making for more sustainable systems.

This conclusion chapter highlights how the main conclusions reached in the thesis have addressed the objectives, as well as giving practical recommendations and suggestions for future research based on those findings. The thesis adopted a water and energy systems approach which required large amounts of data from multiple assets and scales to be assimilated into a coherent framework. Data from the Thames Catchment was used as a case study and the methods presented in the thesis applied to the water infrastructure system within the region. This has allowed the thesis to provide a number of detailed results and recommendations that would have not been achievable without the systems level integration of the wide range of datasets. The approach also highlighted the usefulness of using a systems level perspective to understand specific hard water-energy links within the system, and target more in detail exploration of sub-systems. As highlighted throughout the thesis, the study of interdependencies is key to identifying critical infrastructure hotspots on which to focus.

The thesis started off with Chapter 2 presenting an in-depth introduction to energy in water resources and an overview of methods used to address quantitative energy-water interdependencies. Chapter 3 presented a systems analysis of the energy consumption patterns in water and wastewater infrastructure, addressing Objective 1 in the thesis. The chapter provided a detailed understanding of the drivers of energy consumption and identified hot spots of energy intensity, using the Thames system, in the South East of England, as a case study. An important contribution of the chapter was the provision of Energy Intensities for each functional component of the water use cycle, that can form the empirical basis for more detailed studies. The chapter concluded that in-system differences that may have been less visible in other more traditional, less data-intensive approaches were highlighted by this approach. This is a significant result in that it shows the importance of understanding the contributions from local factors to water infrastructure systems. Specific to the case study, the results showed that clean water treatment is the most energy intensive component of the cycle, but wastewater energy consumption was the fastest growing component. This was thought to be due to changes in effluent quality standards and explored in depth in Chapter 5. The chapter also concluded that specific regions within the Thames area are more energy intensive than other, apparently similar, locations due to high energy-consuming infrastructure. This finding highlights the importance of understanding the geospatial differences in energy and water use. The figures and findings of this chapter form the basis of the more detailed examinations in subsequent chapters.

In Chapter 4, detailed energy costs were integrated into long-term water resources planning and decision-making through a regression-based model, built from the findings in Chapter 3 and addressing Objectives 2 and 3 in the thesis. A Robust Decision Making (RDM) framework was used in conjunction with multi-objective optimization to develop a methodology that can aid decision-makers to choose between different water supply plans when planning long-term water resources management. The analysis concluded that there are important trade-offs between the reliability, capital and operational energy costs of infrastructure options. When operating energy costs are not considered, as has been common in the past, options that are most costly in the long-term could appear as the most attractive. However, the analysis showed that when considering energy consumption, a combination of supply-side measures and more demand management measures ensured lower-cost measures that are better aligned with adaptable and flexible long-term planning. The findings of this chapter illustrate how considering more detailed energy costs in water resources decision making can help make more complete decisions. They can be a basis to encourage more comprehensive analysis of energy costs not only in academia, but also within the water sector and regulators.

The links between wastewater resources and energy were analysed in depth in Chapter 5, also addressing Objectives 2 and 3 from a wastewater perspective. Through quantifying the relationship between the removal of key pollutants, plant extensions and associated energy consumption, the study demonstrated that significant costs could be incurred if there is a need to meet more stringent effluent quality standards. This would be due to additional treatment required in the form of aeration. An analysis of the associated greenhouse gas emissions of such changes showed that unless the decarbonisation of the grid occurs fast enough, there could be significant increases in the greenhouse gas emissions from wastewater treatment in the UK.

Chapter 6 presented a methodological approach to assessing short-term investment decisions in a water pumping and clean water treatment infrastructure network, addressing Objectives 2 and 3 shorter-term perspective. While Chapter 4 focused on robust long-term strategic system water management options, this chapter complements it by focusing on short-term energy efficiency improvements in existing infrastructure. The study used the output of the linear optimization programme to identify bottleneck areas in the network which were not allowing further efficiency gains through a systematic quantitative assessment of the LaGrange Multipliers. A set of capital investments was derived from this to test whether additional operational efficiency gains could be achieved in the system from small capital investments. This was done by applying a Multi-Objective Evolutionary Algorithm. The results showed that the MOEA application was useful to evaluate the trade-off between operational cost optimization and capital investment for a water utility. Greater capital investment provided larger operational savings. The results show how the methodology can be used to help water utilities identify and select key investment portfolios based on specific budgets to reduce operational energy costs.

7.2 Practical recommendations

The development of thesis has benefited from the regular interaction with experts from one of the largest water utilities in the UK. As such, it has been enriched by current interests and concerns in the sector over a wide range of areas and tackles topics that are relevant to current discussions on the development of the water sector. Thus, it has the potential to inform and support decision-making in water resources, both within the water sector and supporting public institutions. This is because it has quantified the specific relationships between energy and water infrastructure in one of the largest water resources management regions of the country. It can provide an empirical basis and benchmark for other academics and industry experts working on understanding the relationship between water and energy. As policy makers become more aware of the interconnectedness of water and energy resources, quantification of the relationships can help them to develop more flexible and adaptable policies that consider impacts. The thesis has also highlighted how interconnected the two resources really are and how a lack of integration in policy can have large implications, for example when considering the greenhouse gas emissions of changing effluent standards. Such findings can help support water utilities to make energy-sensitive wastewater management decisions within the context of changing regulations in the short and long-term, but also regulators themselves when developing such policies.

Furthermore, some of the specific techniques used to incorporate energy into water resources planning used in this thesis can be incorporated in the day-to-day management of water utilities. For example, using optimization techniques to minimize energy costs has not been carried out widely in water utilities, including Thames Water. Practical limitations in methodological transferability, lack of time and experience of tangible benefits that can be obtained from these techniques may have deterred water utilities in the past from adopting optimization techniques. This thesis provides an initial illustration of how optimization techniques can be used in real-world networks, which should lead to further integration between these techniques and those used by water utilities to better inform the management of the water sector. By having been developed in partnership with modelling experts from within Thames Water it also provides an example of how academics can work closely with industry to develop novel approaches to the study of water and energy that can also be beneficial to the sector.

7.3 Future research

The methods presented in this thesis and the associated findings form part of the basis of a growing research field that is aiming to understand the interactions between water and energy systems and future implications. There is significant scope for further research, both in the development of sound methodological approaches to the quantification of energy and water interdependencies, and in the sectoral policy implications.

This thesis has just started to address some of the research challenges that are presented when trying to understand such complex systems. From the author's perspective, the future direction that this area of research should take can be subdivided into five areas:

1. Geospatial understanding of energy and water flows: there is also little work that has focused on the geospatial variance of energy and water infrastructure. Geospatial analysis can provide numerous opportunities to assess risk and develop targeted efficiency efforts. The work carried out in this thesis has begun to reveal interesting spatial variation in energy usage, but has faced challenges with data. Improved data acquisition presents an opportunity for more detailed studies. Khan et al. (2016) show that the field is already moving in this direction. More work that analyses energy and water consumption patterns in a geospatial and temporal manner will provide opportunities for risk reduction and facilitate targeted efforts.
2. Integration of the relationship between water quality and energy into long-term decision-making frameworks: this thesis has mostly focused on the quantification of the energy costs from changing water quantity. As done in this thesis with the quantification of the energy costs of changing water quality for wastewater, future work can follow similar routes with changing clean water quality. As flows change in rivers and concentrations of pollutants change with these flows, more detailed understanding will be required of exactly how changing water quality may influence our ability to supply clean potable water. Some work is already being carried out in this area, such as Mortazavi-Naeini *et al.*, (2017). This is also pertinent to the field of new and emerging contaminants, which may require significant

additional amounts of energy to remove from both drinking water and wastewater.

3. Further exploration into the recovery of energy and the integration of renewable energy into water infrastructure systems: detailed studies that aim to quantify how much energy can realistically be extracted from water infrastructure systems, for example, energy from wastewater treatment or embedded hydropower recovery. Some work has been done so far, but more quantitative work could provide specific, realistic recommendations. Studies focusing specifically on quantifying the real potential of energy recovery technologies from the water sector are needed, and some research has already begun to focus on such synergies, such as Pérez-Sánchez et al. (2017).
4. Further integration of the water sector into the electricity market: There is scope for studies that can draw out specific approaches to further integrate the water sector as a flexible resource for the electricity market. That is, integrating both sectors through providing low-cost electricity to the water sector in exchange for time-specific uses of energy within the sector. This would require very detailed understanding of what elements of water infrastructure systems can be utilised as 'energy storage' and which ones fundamentally require energy at all times to provide clean water. Such studies would need to focus on daily and hourly management and integration of water and electricity systems, and could methodologically be tackled through optimization techniques, reviewed by Mala-Jetmarova et al. (2017).

Many of the avenues for further research mentioned above will require large amounts of data which are currently not publicly available or being collected. More interaction with water utilities and other water sector stakeholders can facilitate the collection of large datasets that can provide useful in tackling some of the above challenges. Thus, future research in this area will need to be developed in collaboration with the water and energy sectors. Communication with utilities can enrich academic studies by providing a real-world perspective on how systems work and up to date practical understanding.

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9. Appendix: Supplementary information

9.1 Water treatment Energy Intensity table

Table 9-1: Energy Intensity (kWh/m^3) for water treatment processes (from Electric Power Research Institute, 2013)

Capacity (m3)	**3,785**	**18,927**	**37,854**	**75,708**	**189,270**	**378,540**	**946,350**
SW pumping	0.038	0.038	0.038	0.038	0.038	0.038	0.038
GW Pumping	0.243	0.243	0.244	0.244			
Rapid mixing	0.011	0.009	0.008	0.008	0.008	0.008	0.008
Flocculation	0.003	0.003	0.002	0.002	0.002	0.002	0.002
Sedimentation	0.004	0.002	0.002	0.002	0.002	0.002	0.002
Chemical feed systems	0.017	0.003	0.008	0.001	0.000	0.000	0.000
Microfiltration (in lieu of sedimentation	0.026	0.026	0.026	0.026	0.026	0.026	0.026
Ultrafiltration	0.211	0.211	0.211	0.211	0.211	0.211	0.211
Reverse Osmosis (brackish water)	1.585	1.575	1.572	1.572	1.20	1.20	0.780
Reverse Osmosis (ocean water)	3.170	3.170	3.170	3.170	3.170	3.170	3.170
Dissolved air flotation	0.029	0.047	0.047	0.048	0.047	0.047	0.047
Air stripping	0.099	0.098	0.099	0.099			
Repumping within treatment plant					0.010	0.010	0.010
Backwash water pumps	0.004	0.003	0.003	0.003	0.004	0.003	0.003
Residuals pumping	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Thickened solids pumping				0.002	0.002	0.002	0.002
Onsite chlorine generation for disinfection	0.022	0.022	0.022	0.022	0.022	0.022	0.022
Plant Production (MGD)		0.000	0.000	0.000	0.000	0.000	0.000
Ozone disinfection	0.037	0.030	0.030	0.020	0.020	0.020	0.020
UV disinfection	0.016	0.016	0.017	0.017	0.017	0.017	0.017
Finished water pumping	0.275	0.281	0.292	0.285	0.258	0.258	0.258
Nonprocess loads (buildings, HVAC, lighting, computers, etc.)	0.079	0.063	0.056	0.048	0.047	0.048	0.048

9.2 Supporting temperature regression results

Table 9-2: Regression model results

Estimated Coefficients:				
	Estimate	SE	tStat	pValue
(Intercept)	0.458649	0.009273	49.45807	2.79E-47
temperature	-0.00131	0.000554	-2.87007	0.005814

Number of observations: 57, Error degrees of freedom: 55; Root Mean Squared Error: 0.0251; R-squared: 0.13, Adjusted R-Squared 0.114; F-statistic vs. constant model: 8.24, p-value = 0.00581

9.3 Multi-objective Genetic Algorithm outputs

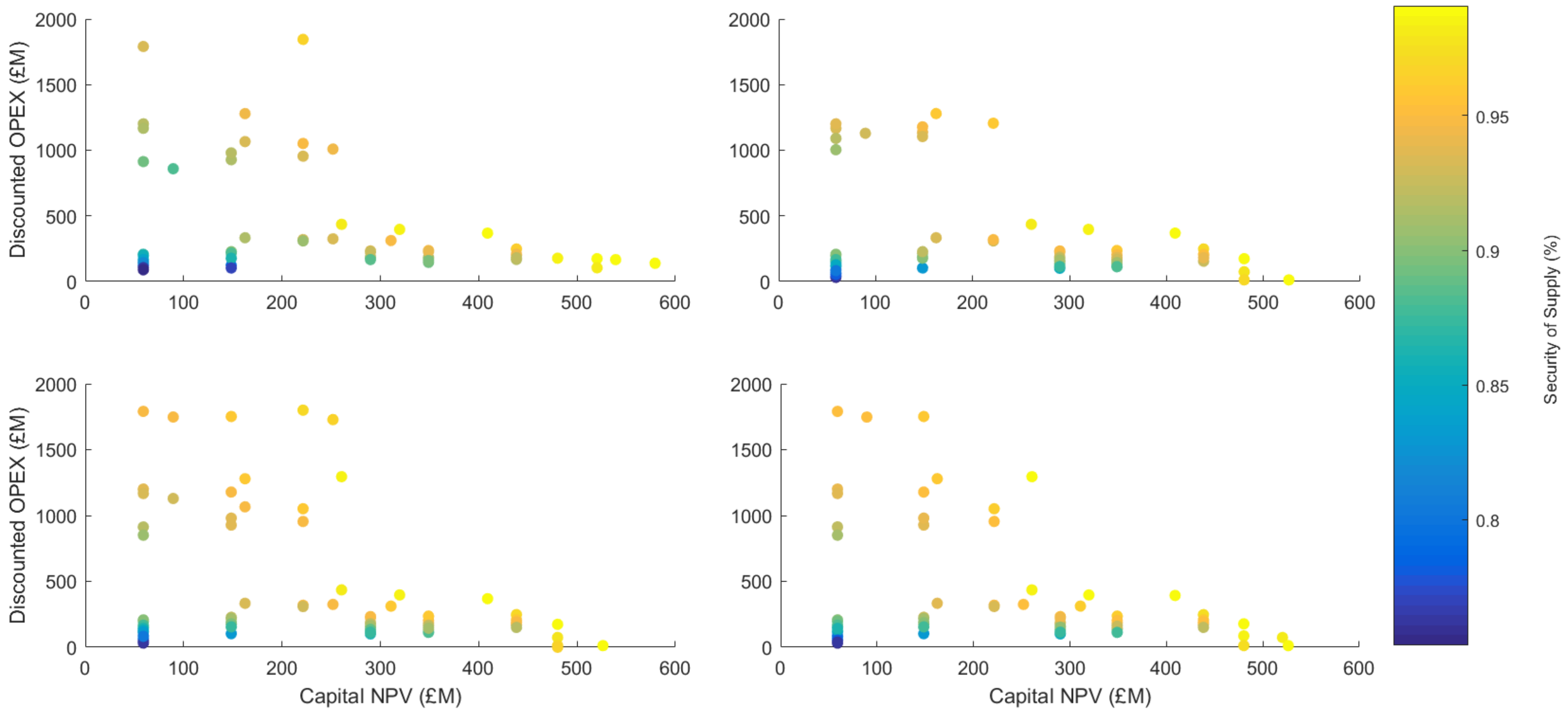

Figure 9-1: Example output runs for multi-objective optimization of CAPEX, OPEX and SS

9.4 Schematic of the London water supply system model

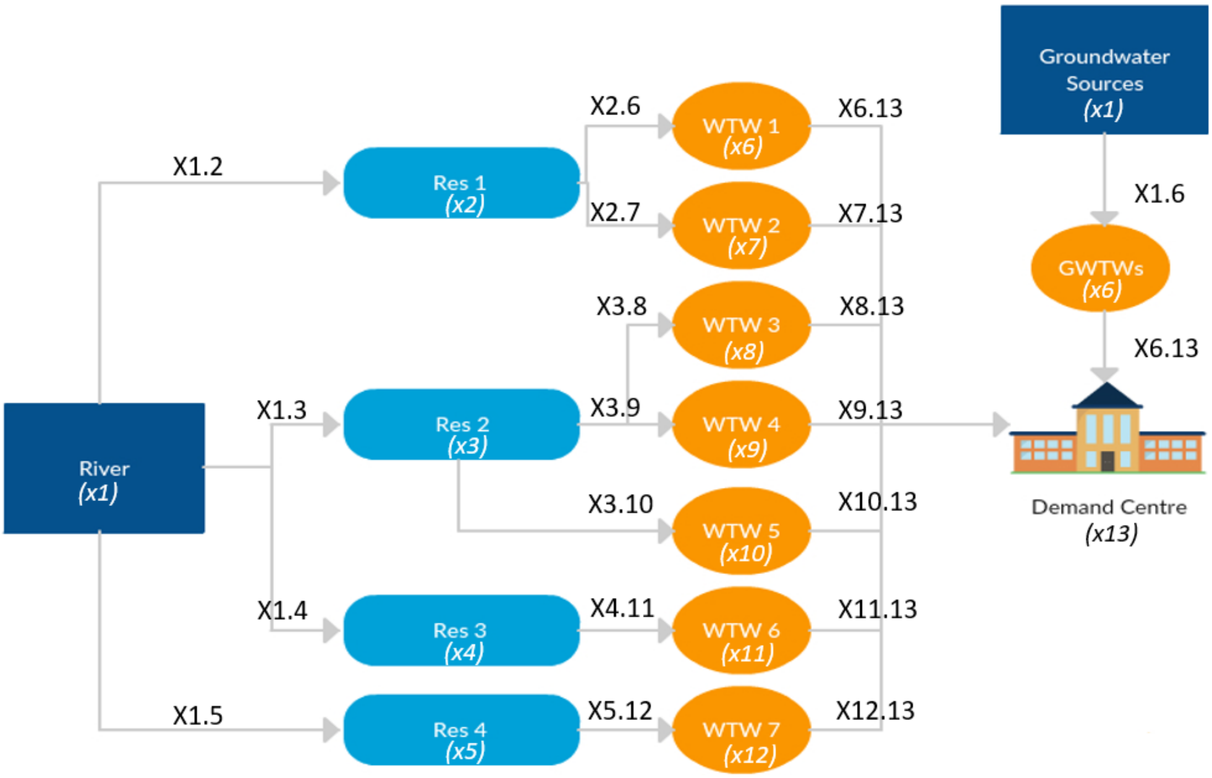

Figure 9-2: Simplified schematic of the London water supply system model.

9.5 Starting Linear Programme parameters

Table 9-3: Starting Linear Programme parameters

Parameter	Starting value
Population	10,000,000 people
Per Capita Demand	160 litres/person/day
Industrial demand	435,000 m^3/day
Energy price	0.125 £/kWh
GHG Conversion factor	0.212 kgCO2e/kWh
Water available for supply	2,385,000 m3/day
GHGs of proposed CAPEX	0.00018-0.00025 tCO2e/£ (depending on option)
Discount Factor	3.5%
Carbon price	21 £/ tCO2e