

**FACULTY OF ENGINEERING
UNIVERSITY OF PORTO**

Decision Support Tools for Water Utility Management: Using Optimisation and Frontier Methods for Continuous Improvement

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FEUP FACULDADE DE ENGENHARIA
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A thesis submitted to the Faculty of Engineering of the University of Porto for the
Doctoral Degree in Industrial Engineering and Management

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*To the memory of my grandparents, Rosa and Manuel,
who left Portugal in the 1930s in search of a better life in Brazil,
and who inspired me to make the journey back.*

*To the memory of my parents, Maria and Herminio,
who provided me with education and inspiration.
The lessons they taught me continue to drive me forward.*

*To Liana, my wife,
whose unwavering support and unconditional love
have been my anchor through this journey
of hard work and perseverance.*

*And to my son, Henrique,
may this thesis be a source for your inspiration.
Follow your dreams and reach for the stars!*

*“E arrepelo a cítara divina.
Agora ou nunca – meu refrão antigo.
O destino destina,
Mas o resto é comigo.”*

Miguel Torga (1907—1995), poeta português.

*“Tente (tente)
E não diga que a vitória está perdida
Se é de batalhas que se vive a vida
Tente outra vez.”*

Raul Seixas (1945—1989), cantor e compositor baiano.

Declaration

- Chapter 4 is based on the paper “A regulatory robust conditional approach to measuring the efficiency of wholesale water supply and wastewater treatment services”, published in *Utilities Policy*. The first author of this paper is Miguel Pereira and it is co-authored with Hermilio Vilarinho, Giovanna D’Inverno, and Ana S. Camanho. The author of this thesis collaborated in this article in the following role categories: conceptualisation, methodology, software, validation, formal analysis, data curation and writing (review and editing) (Pereira et al., 2023).
- Chapter 5 is based on the paper “Water Utility Service Quality Index: A customer-centred approach for assessing quality of service in the water sector”, under revision in *Socio-Economic Planning Sciences*. The first author of this paper is Hermilio Vilarinho and it is co-authored with Miguel Pereira, Giovanna D’Inverno, Henriqueta Nóvoa and Ana S. Camanho.
- Chapter 6 is based on the paper “The measurement of asset management performance of water companies”, published in *Socio-Economic Planning Sciences*. The first author of this paper is Hermilio Vilarinho and it is co-authored with Giovanna D’Inverno, Henriqueta Nóvoa and Ana S. Camanho (Vilarinho et al., 2023c).
- Chapter 7 is based on the paper “Performance analytics for regulation in retail water utilities: guiding asset management by identifying peers and targets”, published in *Utilities Policy*. The first author of this paper is Hermilio Vilarinho and it is co-authored with Giovanna D’Inverno, Henriqueta Nóvoa and Ana S. Camanho (Vilarinho et al., 2023d).
- Chapter 8 is based on the paper “Optimisation models for project selection in asset management: an application to the water sector”, published in *International Transactions in Operational Research*. The first author of this paper is Hermilio Vilarinho and it is co-authored with Flávia Barbosa, Henriqueta Nóvoa, Jaime Gabriel Silva, Luciana Yamada and Ana S. Camanho (Vilarinho et al., 2023b).

Preliminary results of this study are published in *Revista de Ativos de Engenharia* (in Portuguese) in which Hermilio Vilarinho is the first author and Flávia Barbosa, Henriqueta Nóvoa, Jaime Gabriel Silva and Ana S. Camanho are co-authors (Vilarinho et al., 2023a).

Abstract

This thesis covers the development of decision-support tools to support the management of water systems. The proposed models incorporate various optimisation techniques, including Data Envelopment Analysis (DEA), Directional Distance Functions (DDFs), Mixed-Integer Linear Programming (MILP) models, and Evolutionary Algorithms. The decision support tools proposed in this thesis aim to assess cost-efficiency, service quality, asset management practices, and infrastructure investment selection in water systems. Consequently, the results obtained reflect the utilities' accomplishments from multiple perspectives.

The thesis covers five main topics. The first topic involves determining the optimal operating costs of a group of water supply and wastewater utilities. DEA is utilised to undertake this benchmarking exercise in collaboration with a regulatory authority for the sector. The use of robust and conditional approaches for the estimation of efficiency helps mitigate the effect of extreme performers and adjust the efficiency scores to the context in which the utilities operate.

The second topic focuses on measuring the quality of the service provided by water utilities. A synthetic performance indicator is introduced to reflect the assessment of service quality, inspired by the framework developed by the *World Bank*. According to this framework, utility performance is expressed by the dimensions of *reliability*, *safety*, *inclusiveness*, *transparency* and *responsiveness*. The approach proposed uses directional Benefit-of-the-Doubt (BoD) composite indicator models.

The third topic explores asset management performance. Two Benefit-of-the-Doubt composite indicators are introduced, reflecting both the managerial practices and infrastructure operation conditions, based on the metrics collected by the sector's regulator authority. The method is applied to a pool of wholesale water supply companies, and the performance of the utilities is appraised for a five-year period. The effect of contextual variables is also evaluated using conditional formulations of BoD models.

The fourth topic is focused on the identification of the appropriate peers and the most suitable targets in terms of asset management achievements. The Benefit-of-the-Doubt composite indicators developed for the third topic are enhanced to allow the identification of peers and targets. A sample of retail water operators is used to test the developed tools.

The fifth topic is dedicated to the identification of efficient portfolios of infrastructure investment projects. Mixed-Integer Linear Programming (MILP) models are constructed to allow the optimum allocation of available capital or to maximise infrastructure condition. An evolutionary algorithm is employed to determine intermediate solutions that provide alternative portfolios. These methods are applied to a pumping station infrastructure of a Portuguese water company, and can guide decision-makers in the selection of the investments that should be undertaken.

The management of water resources is becoming an increasingly pressing issue in light of climate change, limited resources to meet human needs, and deteriorating infrastructure with mounting capital investment needs. The present research presents innovative decision-making models that aim to respond to these challenges and guide water systems management. Moreover, some of the decision support tools developed in this work can potentially be adapted for use in other sectors, thereby extending the applicability of these models beyond the water sector.

keywords: Asset management, Benefit-of-the-Doubt, Benchmarking, Capital investment planning, Composite indicator, Data Envelopment Analysis, Directional Distance Functions, Efficiency Analysis, Evolutionary Algorithms, Mixed-integer Linear Programming, Performance Indicator, Project Selection, Water Regulation, Water Supply, Wastewater Treatment, Water Systems.

Resumo

Esta tese abrange o desenvolvimento de ferramentas de apoio à decisão para dar suporte à gestão de sistemas de água. Os modelos propostos incorporam várias técnicas de otimização, incluindo Análise Envoltória de Dados (DEA), Funções de Distância Direcional (DDFs), Modelos de Programação Linear Inteira Mista (MILP), e Algoritmos Evolutivos. As ferramentas de apoio à decisão propostas nesta tese visam avaliar a eficiência de custos, a qualidade do serviço, as práticas de gestão de ativos e a seleção de investimentos em infraestruturas em sistemas de água. Consequentemente, os resultados obtidos refletem o desempenho das empresas de abastecimento de água e de tratamento de águas residuais a partir de múltiplas perspectivas.

A tese inclui cinco tópicos principais. O primeiro tópico envolve a determinação dos custos operacionais ótimos de um grupo de empresas de abastecimento de água e de tratamento de águas residuais. Utilizou-se DEA para efetuar este exercício de avaliação comparativa em colaboração com uma autoridade reguladora do sector. A utilização de abordagens robustas e condicionais para a estimação de eficiência ajuda a atenuar o efeito dos desempenhos extremos e a ajustar as avaliações de eficiência ao contexto em que as empresas de serviços públicos operam.

O segundo tópico centra-se na medição da qualidade do serviço prestado pelas empresas de água e saneamento. É introduzido um indicador sintético de desempenho para refletir a avaliação da qualidade do serviço, inspirado na abordagem desenvolvida pelo Banco Mundial. De acordo com essa abordagem, o desempenho das empresas é expresso pelas dimensões de *confiabilidade*, *segurança*, *inclusividade*, *transparência* e *responsividade*. O método proposto utiliza modelos direcionais de indicadores compósitos do tipo Benefício da Dúvida (BoD).

O terceiro tópico explora o desempenho em gestão de ativos. São introduzidos dois indicadores compósitos do tipo Benefício da Dúvida, refletindo tanto as práticas de gestão como as condições de operação das infraestruturas, com base nas métricas recolhidas pela autoridade reguladora do setor. O método é aplicado a um conjunto de empresas de abastecimento de água em alta, e o desempenho das empresas é avaliado para um período de cinco anos. Além disso, o efeito das variáveis contextuais é estimado usando formulações condicionais dos modelos BoD.

O quarto tópico tem foco na identificação dos *benchmarks* apropriados e dos objetivos mais adequados em termos dos resultados em gestão de ativos. Os indicadores compósitos do tipo Benefício da Dúvida desenvolvidos para o terceiro tópico são aprimorados para permitir a identificação de *benchmarks* e objetivos a atingir. Uma amostra de operadores de água em baixa é utilizada para testar as ferramentas desenvolvidas.

O quinto tópico é dedicado à identificação de portfólios eficientes de projetos de investimento em infraestruturas. Foram propostos modelos de programação linear inteira mista (MILP) de modo a permitir a melhor aplicação possível do capital disponível ou a maximizar a condição das infraestruturas. Foi usado um algoritmo evolutivo para determinar soluções intermédias que fornecem portfólios alternativos. Esses métodos foram aplicados a uma infraestrutura de estação de bombagem de uma empresa portuguesa de fornecimento de água, e permitem orientar os decisores na seleção dos investimentos a executar.

A gestão dos recursos hídricos está a tornar-se uma questão cada vez mais urgente à luz das alterações climáticas, dos recursos limitados para satisfazer as necessidades humanas, bem como da deterioração das infraestruturas, que requerem investimentos de capital muito significativos devido ao envelhecimento dos ativos. A presente investigação apresenta modelos inovadores para a tomada de decisão, que visam responder a esses desafios e guiar os esforços de melhoria contínua no setor de água. Além disso, alguns dos instrumentos de apoio à decisão desenvolvidos neste trabalho podem ser potencialmente adaptados para utilização em outros setores, alargando assim a aplicabilidade destes modelos para além do setor da água.

Palavras-chave: Gestão de Ativos, Benefit-of-the-Doubt, Benchmarking, Planeamento de Investimento de Capital, Indicador Compósito, Data Envelopment Analysis, Funções de Distância Direcional, Análise de Eficiência, Algoritmos Evolutivos, Programação Linear Inteira Mista, Indicador de Desempenho, Seleção de Projectos, Regulação de Água, Abastecimento de Água, Tratamento de Águas Residuais, Sistemas de Água.

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Acronyms

AA	Abastecimento Público de Água (Public Water Supply)
AMMI	Asset Management Maturity Index
AR	Saneamento de Águas Residuais Urbanas (Urban Wastewater Sanitation)
ASI	Asset Service Index
BCG	Boston Consulting Group
BoD	Benefit-of-the-Doubt
CapEx	Capital Expenditure
CI	Composite Indicator
CRS	Constant Returns to Scale
DDF	Directional Distance Function
DEA	Data Envelopment Analysis
DMU	Decision-Making Unit
DSS	Decision Support Systems
DST	Decision Support Tools
EPA	Environmental Protection Agency
ERSAR	Entidade Reguladora dos Serviços de Água e Resíduos (Water and Waste Services Regulatory Authority)
EU	European Union
FDH	Full Disposal Hull
ICV	Infrastructure Current Value
IHP	International Hydrological Programme
IoT	Internet of Things
IRC	Infrastructure Replacement Cost
ISO	International Organization for Standardization
IVI	Infrastructure Value Index
MCDA	Multiple-criteria decision analysis
MCDM	Multiple-criteria decision-making
MILP	Mixed Integer Linear Programming
NPV	Net Present Value
NSGA	Non-dominated Sorting Genetic Algorithm
NUTS	Nomenclatura das Unidades Territoriais para Fins Estatísticos (Nomenclature of Territorial Units for Statistics)
OECD	Organisation for Economic Co-operation and Development
OPEX	Operational Expenditure
PDCA	Plan-Do-Check-Act
PS	Pumping Station
RC	Replacement Cost
RISI	Resource and Infrastructure Sustainability Index
RL	Residual Life
SDG	Sustainable Development Goals
SFA	Stochastic Frontier Analysis
SM	Serviços Municipalizados (Municipalised Services)
SMAS	Serviços Municipalizados de Água e Saneamento (Municipal Water and Sanitation Services)
SUWM	Sustainable Urban Water Management
TC	Technical Committee
TFA	Thick Frontier Approach
UL	Useful Life
UN	United Nations
UoF	Utility of the Future
UWC	Urban Water Cycle
VRS	Variable Returns to Scale
WS	Water Supply
WSP	Water Safety Plans
WT	Wastewater Treatment

CHAPTER 1

Introduction

This chapter contextualises the research topic investigated in this thesis. Section 1.1 states the research motivation and the reasons for examining the water sector. Section 1.2 presents the research objectives of the thesis. Section 1.3 showcases the main contributions of the thesis. Finally, the thesis outline is described in section 1.4.

1.1 Motivation

Access to safe drinking water, sanitation, and hygiene services is critical for human health. However, current progress towards achieving universal access to these services is slower than required, and billions of people are at risk of being left without them. The challenges to sustainable water management are vast and complex, with increasing demand due to population growth, urbanisation, and pressure from agriculture, industry, and energy sectors. Decades of misuse, poor management, and contamination have led to water stress and degraded water-related ecosystems, with far-reaching impacts on human health, economies, and food and energy supplies. Urgent action is needed to reverse this trend and ensure sustainable access to water resources for all.

According to the United Nations World Water Assessment Programme Report (WWAP, 2016), more than 40% of the global active workforce, which is over one billion jobs, heavily rely on water. These water-intensive jobs are present in various sectors, such as agriculture, forestry, inland fisheries, mining, power generation, water supply and sanitation, as well as manufacturing industries like food, pharmaceuticals, and textiles. Moreover, over one-third of the world's total active workforce, representing another billion jobs, are moderately water-dependent. These jobs are found in sectors such as construction, recreation, transportation, and manufacturing and transformation industries such as wood, paper, rubber/plastics, and metals.

The United Nations has set forth the 2030 Agenda for Sustainable Development, which requires countries to implement a structured process of tracking and assessing their progress towards achieving the goals and targets. This involves using standardised global indicators that provide a framework for measuring and evaluating performance. Monitoring and review processes are vital for promoting transparency, accountability, and continuous improvement towards sustainable development. Goal 6 of the 17 Sustainable Development Goals (SDGs) established by the United Nations (UN) focuses on water and sanitation, aiming to provide safe and accessible drinking water and sanitation for everyone. A closer look at the United Nations' SDGs reveals that all of them,

in a certain way, prioritise the sustainable use and consumption of water, making Goal 6 the centrepiece for achieving all SDGs. As such, all SDGs can be considered interconnected with Goal 6. This relationship is illustrated using a water-centric figure (Figure 1.1) presented by Makarigakis and Jimenez-Cisneros (2019). The figure effectively displays how water is central to achieving sustainable development across all sectors.



Figure 1.1: The water centric 17 Sustainable Development Goals (Makarigakis and Jimenez-Cisneros, 2019)

The UN Sustainable Development Goals Report (United Nations, 2022) shows that there has been an increase in the proportion of the global population with access to safely managed drinking water and sanitation services. However, there are still significant challenges to overcome. As of 2020, 2 billion people still lack access to safe drinking water, with 1.2 billion people lacking even basic service, and the majority of those without access to drinking water live in rural areas and least developed countries. Similarly, access to safely managed sanitation services remains a challenge, with 2.8 billion people lacking access as of 2020. While the world is on track to eliminate open defecation by 2030, the increase in access to hand washing facilities with soap and water has been minimal. Despite improvements, over 829,000 people still die each year from diseases caused by unsafe water, inadequate sanitation, and poor hygiene practices. To achieve universal coverage by 2030, the rate of progress would need to increase fourfold. While a vast collection of “sustainable approaches” have been conceptualised and implemented in the water industry since the publication of UN SDGs, there is still room for improvement to maximise the tangible benefits they provide (Silva, 2022).

Water and wastewater systems are complex and essential infrastructure systems for societies,

consisting of pipes, valves, pumps, and reservoirs. However, managing the reliability of these complex networks spread over large territorial areas, while keeping operational costs under control, is a challenging task. Interruptions to these systems can have significant social and legal implications, as failures can happen unexpectedly and may have cascading effects on other systems. The consequences of failures in a water system can be extensive, causing damage to adjacent structures, disrupting transportation and commerce, and impacting urban life. These asset-intensive systems require effective management of asset portfolios to sustain their level of service, and maintenance and preservation initiatives must be in place to minimise interruptions and breakage events (Mazumder et al., 2018).

Given the essential role of water systems in our daily lives and the challenges faced by these critical infrastructure networks, it is imperative that we prioritise and accelerate efforts to improve management practices. This thesis aims to address various aspects of water supply and sanitation utilities, ranging from cost-efficiency to service quality and asset management, in order to reach their critical goals. To achieve these objectives, a set of analytical tools and strategies is proposed to guide decision-making processes. These tools support decision-makers in selecting areas to focus their efforts and identifying the most effective alternatives to ensure the greatest possible gains with existing resources. The tools developed are based on frontier methods and optimisation techniques, which promote transparency through methodological rigour in data treatment. By leveraging advanced data analytics tools and techniques, water utilities can gain deeper insights into their operations and identify opportunities for continuous improvement.

It should be noted that this thesis is structured as a compilation of papers, and thus certain ideas and terminology may be reiterated across different sections.

1.2 Research goals

The main objective of this thesis is to develop innovative models, using mathematical programming techniques, with a particular focus on optimisation and frontier methods, to tackle management issues faced by water utilities. The goal is to provide support for evaluations both at the organisational and industry levels. To ensure the practical relevance of the proposed developments, real-world data from water utilities are utilised in illustrative applications.

This thesis fits into the research of frontier methods and optimisation. The work gives a particular emphasis to the use of the Data Envelopment Analysis (DEA) technique, including the use of the Benefit-of-the-Doubt (BoD) approach, for organisational performance measurement. Additionally, the research applies optimisation methods, namely Mixed-Integer Linear Programming (MILP) and evolutionary methods. In this thesis, the mathematical models developed are referred to as Decision Support Tools (DSTs). These tools, along with the results of their real-world applications and the interpretation of those results, constitute the primary outcomes of the work.

The connecting thread of this thesis is depicted in Figure 1.2. This figure illustrates the connections between the pressing issues faced by water utilities, the challenges they must address,

the methods employed in the thesis to build decision support tools, and the resultant utilities' decision-making processes facilitated by the developed tools.

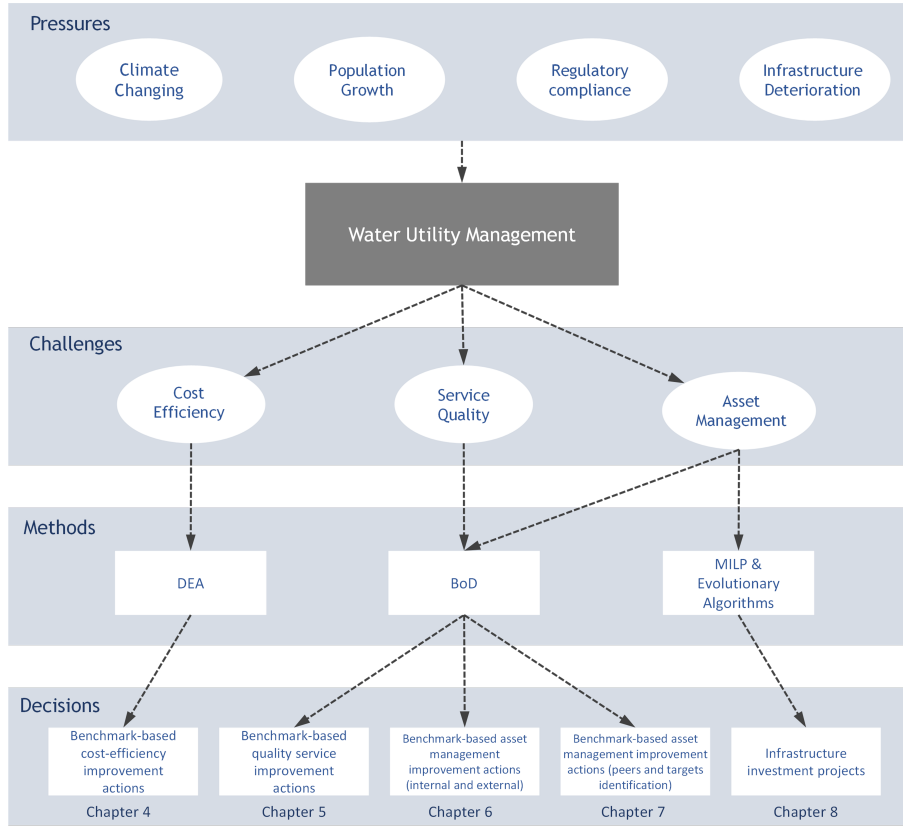


Figure 1.2: Connecting thread of the thesis

The pressing issues encompass climate change, population growth, regulatory compliance, and infrastructure deterioration. These issues serve as motivating factors for water utilities to enhance their management practices and tackle significant challenges head-on.

Within this thesis, the challenges explored revolve around cost-efficiency, service quality, and asset management. These challenges, in turn, drive the development of decision support tools based on DEA, BoD, MILP and evolutionary methods. These tools are specifically designed to assist utilities in making informed decisions regarding continuous improvement actions.

The research goals of this thesis are closely aligned with each decision process facilitated by the developed tools, ensuring that the objectives of the study are interconnected with practical applications and real-world utility scenarios.

In the following paragraphs, the research goals of the thesis are introduced.

The first research goal is to develop a model to assess the optimal operational cost (OPEX) level of a group of wholesale water utilities in a benchmarking exercise. The proposed model is used to guide decision-making to promote improvements in cost management within utilities.

The second research goal is to build an assessment tool capable of measuring the service quality performance of water and wastewater companies. Based on the benchmarking results, companies and the regulatory authorities can make informed decisions regarding improvement actions aiming at enhancing service quality.

The third research goal is to develop an assessment model that facilitates both internal and external benchmarking practices regarding asset management. This model evaluates the operational results and management features of utilities in relation to their infrastructure. Internal benchmarking compares a utility's performance across different years, while external benchmarking compares different utilities against each other. The tools developed through this research can assist utilities and regulatory authorities in enhancing utility results.

The fourth research goal is to provide a decision tool that enables the identification of the most suitable peers and achievable targets for asset management in water utilities. The models developed can be useful to reveal effective practices in asset management and help companies achieve better results.

Lastly, the fifth research goal to propose tools that can support managers in determining the most suitable set of infrastructure projects to undertake. These decision support tools contribute to efficient project selection and execution.

1.3 Main contributions

This section highlights the most significant and innovative aspects of this thesis that represent advancements beyond the current state-of-the-art in scientific research. It also describes the practical contributions made by the empirical studies reported in the thesis, based on real-world utility data from the water sector. Those case studies offer concrete examples of how the developed methods can drive positive change in the water sector, demonstrating their practical impact on decision-making process. The following paragraphs outline the specific contributions of each case study, along with the information regarding the sampling used for each case. The contributions of each case study are referenced to their respective chapters in the thesis, as indicated in Figure 1.2.

Chapter 4 presents a novel approach for evaluating the efficiency of water utilities that takes into account their peers' performance, as well as their operational context. The study uses robust and robust conditional order-m Data Envelopment Analysis (DEA) models to assess the optimal OPEX level of water supply and wastewater treatment services operating in the wholesale market. A standout feature of this work is its emphasis on collaboration with the regulatory authority. This has allowed for the development of a practical decision-making tool that can guide improvements in cost-efficiency within the water sector, supporting the activities of both utility managers and regulators. The data used in this study was collected from the annual results of ten wholesale water supply utilities and 12 wholesale wastewater utilities, between 2017 and 2021.

Chapter 5 provides an innovative method for evaluating the quality of water utility services, based on the users' perspective framework introduced by the World Bank. This novel approach

utilises the Benefit-of-the-Doubt (BoD) technique to construct composite indicators, and introduces the Deck-of-cards method (DCM) to develop a transparency metric. The study also provides utilities and regulators with a practical tool for assessing service quality and directing continuous improvement actions. The data utilised in this study was obtained from the annual reports of ten wholesale water supply and 12 wholesale wastewater utilities from Portugal. The data collection period extended from 2016 to 2021.

In Chapter 6, a bi-dimensional asset management evaluation framework is presented, based on Benefit-of-the-Doubt (BoD) composite indicators. This method is novel in the literature, as it utilises metrics collected by a regulatory authority from utilities to construct composite indicators with a focus on asset management practices. Additionally, the method provides a means of benchmarking utility performance over time, reinforcing its practical relevance in the water sector. The data used in this study was collected from annual reports of ten wholesale water supply utilities from Portugal, spanning a period of five years, specifically from 2016 to 2020.

Chapter 7 introduces a method for identifying peers and targets in water retail utilities with regards to asset management practices based on BoD models, which has not been explored in the literature. By identifying suitable peers for benchmarking in asset management, utilities can analyse sector best practices and benefit from them. The method also establishes individual targets for each utility, based on the metrics considered in the assessment, which are more realistic than the general goals established by the regulatory authority for the whole sector. This facilitates improvement actions and strengthens the practical application of the method. The sample employed in this study consisted of 223 retail water utilities in Portugal, and the data collected pertained to the year 2020.

In Chapter 8, a new method is presented for selecting and prioritising capital projects in water utility infrastructures, using the widely recognised Infrastructure Value Index (IVI). This method utilises optimisation techniques, namely multi-integer linear programming (MILP) and evolutionary algorithms, to facilitate investment project portfolio decisions. The IVI has not previously been used in optimisation methods in the literature, which characterises the innovative feature of this study. The procedures developed in this work can be utilised by water utilities to guide investment decisions in infrastructure, supporting enhanced initiatives in asset management. The sample utilised in this study was obtained from the infrastructure of a water utility based in Portugal.

1.4 Thesis outline

The remainder of this thesis comprises the following chapters:

Chapter 2 examines the pressing issues faced in managing modern water systems, such as climate change, population growth, regulatory demands and deteriorated infrastructure. These issues underscore the significance and urgency of this research, as it seeks to provide innovative solutions for enhancing the efficiency and effectiveness of water system management in overcoming the challenges of cost-efficiency, service quality and asset management.

Chapter 3 provides a comprehensive introduction to the critical concepts related to the decision support tools that will be explored in greater detail throughout the thesis. These tools are based on frontier methods such as Data Envelopment Analysis (DEA), including the Benefit-of-the-Doubt (BoD) approaches and optimisation techniques. Furthermore, the chapter showcases decision support tools as a means of overcoming these obstacles and achieving desired goals. The tools can help decision-makers optimise water management strategies and make informed choices, paving the way for more sustainable and resilient water systems.

Chapters 4, 5, 6, 7 and 8 are dedicated to the empirical studies focusing on achieving the research goals as indicated in Section 1.2, and detailed in Section 1.3. The investigations conducted within these chapters have led to the publication or submission of papers to reputable journals, with the intention of making valuable contributions to the existing literature and fostering engagement within the scholarly community.

Chapter 9 presents the main conclusions of this thesis, including the contributions achieved and the research limitations. Insights extracted from the illustrative applications and directions for future research are also highlighted.

Challenges and trends in water utility management

This chapter provides an overview of the water utility management issues addressed in this thesis and their relevance in the current context. The importance of this research lies in the urgent need for improved water management practices, as safe and reliable water supply and effective wastewater treatment are crucial for public health and environmental sustainability. The chapter discusses the pressing issues in water system management, such as climate change, population growth, infrastructure deterioration and regulatory compliance, which require a multidisciplinary approach for effective management strategies. These issues create challenges that need to be addressed by management in various perspectives such as cost-efficiency, service quality and asset management. Moreover, the chapter discusses the emerging trends in water utility management.

2.1 Introduction

Water and wastewater systems are collectively denoted as “water utilities” (ISO, 2007a,b,c). The management of these utilities involves overseeing and maintaining water supply and sanitation systems, encompassing a wide range of activities such as planning, designing, constructing, operating, and maintaining water infrastructure, as well as managing the financial, legal, and regulatory aspects of water services. It is essential for all utilities, regardless of their size or location, to manage every aspect of their operations effectively. This is critical for their long-term sustainability and for maintaining the communities that they serve strong, safe, and sustainable (Bloetscher, 2011). Essentially, good management practices should be viewed as tools to enhance utilities’ efficiency and quality of service and foster continuous improvement. The management processes serve as an umbrella, protecting managers from the environment and helping them navigate through their work. Effective water utility management is a challenging task, as it involves a wide range of activities, including setting goals and targets, monitoring and evaluating performance, managing resources, and engaging with stakeholders. It also requires the use of innovative technologies and tools to improve operations and reduce costs (AWWA, 2004).

The idea of *water security* can be taken as the ultimate objective of managing water systems at the utility level. Water security is widely recognised as a crucial concept in the pursuit of sustainable practices in the water sector (Nazemi and Madani, 2018). However, as noted by Marcal et al. (2021), there is no consensus on a specific definition of water security. In their review of

various frameworks on this concept, these authors advocate for the use of the United Nations' definition, which defines water security as "the capacity of a population to safeguard sustainable access to adequate quantities of acceptable quality water for sustaining livelihoods, human well-being, and socio-economic development; for ensuring protection against water-borne pollution and water-related disasters; and for preserving ecosystems in a climate of peace and political stability."

According to Leigh and Lee (2019), managing sustainable urban water systems involves finding a delicate balance that addresses a multitude of priorities, including (i) social objectives for a fair distribution of water resources and costs, (ii) economic objectives for ensuring water quantity and quality, and (iii) environmental objectives for providing long-term water supply. The conflicts between these priorities should be minimised. Furthermore, the focus should be on creating water systems that are both sustainable and responsive, meaning that they are resilient to disturbances and possess the ability to adapt and evolve to maintain essential functions while guiding their own adaptation toward a more desirable state. This paradigm is widely discussed in the literature and referred to as *Sustainable Urban Water Management (SUWM)* (Marlow et al., 2013; Brown and Farrelly, 2009; Keath and Brown, 2009; Hurlimann and Wilson, 2018).

Overall, water utility management is a complex and demanding task, but it is essential for ensuring that water resources are used sustainably and that communities have access to the water and sanitation services they need to thrive.

The remainder of this chapter is structured as follows: Section 2.2 presents the main characteristics of water utilities, Section 2.3 discusses the critical challenges in the management of water utilities, Section 2.4 presents the emerging trends for managing water utilities and Section 2.5 provides the conclusions.

2.2 Water supply and wastewater utilities

This section aims to characterise water utilities for water supply and sanitation and describe their main elements.

Urbanisation has a profound impact on the natural water cycle, leading to a more intricate hydrological cycle in urban areas due to various human activities and interventions. This complex hydrological cycle in urban areas is commonly known as the urban water cycle (UWC), and it comprises several components and pathways, as depicted in Figure 2.1. According to Marsalek et al. (2008), the UWC is a valuable framework for studying the water balance in urban areas. The high level of interaction among the elements of the UWC, as seen in Figure 2.1, underscores the need to understand these interactions for effective urban planning and integrated management of urban water systems. Pinto et al. (2023) emphasise that integrated management of the UWC is crucial for ensuring the sustainability and resilience of urban water systems. To achieve this, the system must be viewed as a whole, considering the inter-dependencies of the various elements. Although these interactions can create complexity, they also present opportunities for synergies and gains in integrated management. For instance, treated wastewater can be used for non-potable purposes, reducing the demand for fresh water resources. Franco-Torres et al. (2021) outline that with the

adoption of a new approach that emphasises the coordinated management of water systems, it is possible to repurpose stormwater as potable water, assess leaky sewers as source of pollution for water supply, and take wastewater as a valuable resource for replenishing groundwater aquifers. As discussed by McConville (2023), there is a growing trend in the sanitation industry to view wastewater as a resource rather than waste. This has resulted in proposals and implementations of separate collection systems for various wastewater fractions. Separating wastewater by levels of contamination can simplify the treatment processes since the volumes requiring advanced treatment will be only a fraction of the total wastewater volumes.

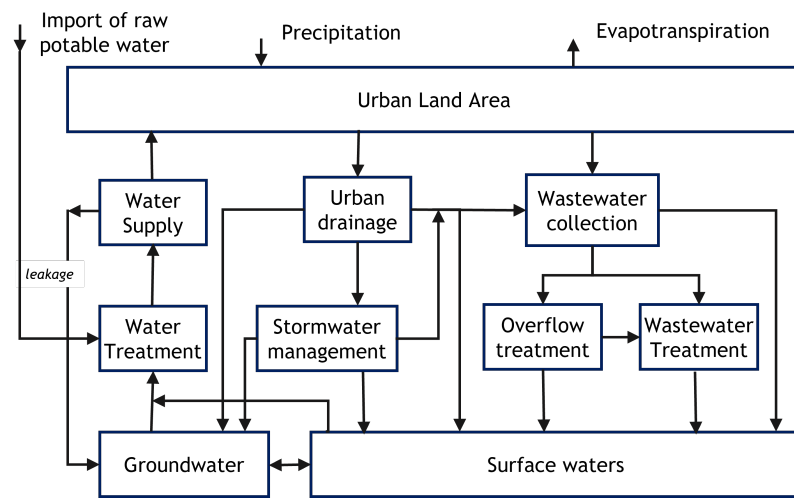


Figure 2.1: Urban Water Cycle (Marsalek et al., 2008)

Although the need for integrating the activities of the UWC has been widely discussed, the structure of the water industry varies significantly across the globe in terms of activities undertaken by individual businesses, size, customer base, private sector involvement, competition, regulation, and oversight. Water businesses typically perform a range of activities including water collection, transfer, treatment, distribution, sewerage collection and treatment, irrigation, and drainage. Various factors, such as the source of water, geography, geology, topography, customer type, demand, and density, influence the activities undertaken by water businesses. According to Abbott and Cohen (2009), in many small to medium-sized markets, water businesses operate as vertically integrated monopolies, while larger metropolitan areas may present several vertically integrated entities coexisting with separate local distribution networks.

Abbott and Cohen (2009) highlight the significant capital costs associated with water supply networks as a major barrier to competition. Compared to energy distribution systems where distribution infrastructure costs represent only 40% of the supplied electricity, the cost of water and distribution systems accounts for two-thirds of the water supply, making it expensive to duplicate and contributing to the creation of natural monopoly conditions. These factors make it difficult for

new players to enter the market and offer competitive prices, which can ultimately lead to higher prices and reduced innovation.

Water supply and wastewater services can be managed jointly or as separate “management entities”. Examples of typical operational stages found in infrastructures of water supply and wastewater utilities can be seen in Figure 2.2a and 2.2b, respectively.

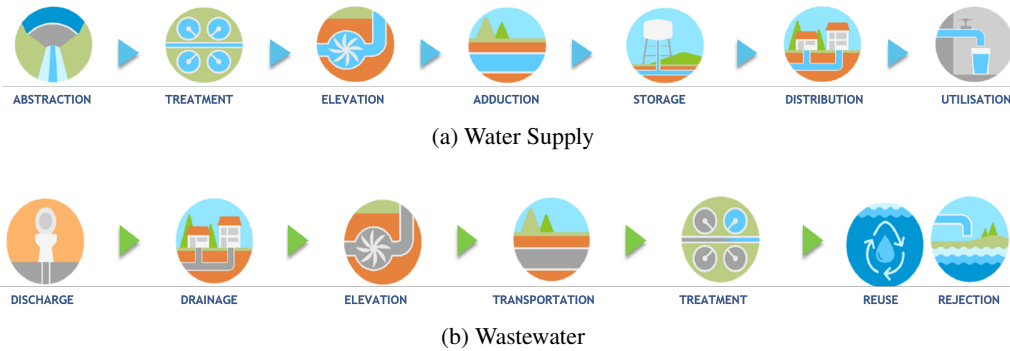


Figure 2.2: Typical operational stages of water and wastewater utilities (ERSAR, 2021a)

As seen in Figure 2.2a, water supply utilities collect raw water from various sources such as rivers, lakes, ground water, underground aquifers and reservoirs. Most of these water sources can not be directly consumed, so they must be treated. The choice of an appropriate treatment method depends on various factors, with the raw water quality being the primary driver. Filtration, coagulation, and disinfection are some of the possible treatment methods that can be employed to achieve suitable water quality (Adedeji and Hamam, 2020).

Pumping is utilised to facilitate the movement of water, including to locations at higher elevations, by adding energy to the flow and raising pressure levels. They are applicable in various sections of a water supply system, such as conveying untreated water from the source to a treatment facility, pressurising water to be distributed to the system, and enhancing pressure in segments of the system that experience low pressure (i.e., booster pumps). Adduction systems are usually employed to convey raw water to treatment and treated water to storage tanks.

Storage tanks are used for several purposes, such as meeting variable demands, balancing operating pressure, and serving as a reserve for emergency and firefighting needs.

Distribution networks consist of various pipe types, such as water transmission mains that transfer potable water from storage facilities to different parts of the system, including supply pressure zones or district metered areas. Distribution pipes, which have a smaller diameter than transmission mains, distribute potable water within local areas. Supply/customer connection pipes connect individual end-user properties to the water distribution system (Farmani and Sweetapple, 2023).

In wastewater systems, as displayed in Figure 2.2b, the drainage or collection of wastewater is primarily done through piped sewer systems. Depending on the terrain and size of the area being served, pumping stations can be required in the collection and transportation systems. Conventional wastewater treatment uses physical, biological, and chemical processes to purify the incoming wastewater in response to increasingly stringent treatment standards. Initially, treatment focused on removing suspended solids and pathogens, known as primary treatment. The development of secondary treatment processes in the 1960s was in response to the need for reduction of dissolved organic matter. In the 1970s, tertiary treatment processes emerged for phosphorus and nitrogen removal, with widespread adoption in the 1990s. Today, the majority of high-income countries' wastewater treatment plants have at least a secondary treatment, if not a tertiary treatment. However, it is important to note that treatment levels vary between countries.

The final stage of the sanitation service chain involves either rejection or reuse of treated products. Conventional urban sanitation systems in high- and middle-income countries generally produce effluent water and sewage sludge, which are often released into local waterways. However, reuse of treated wastewater is becoming more common, especially in water-stressed areas. In Europe, only slightly over 2% of the treated urban wastewater effluent is currently being reused. Nevertheless, the European Commission is taking steps to encourage and facilitate water reuse by developing rules and incentives. In contrast to Europe, Singapore, a country facing water scarcity, has made significant progress in water reuse. Treated wastewater is used for direct non-potable use and indirect potable use, meeting over 40% of its total water demand. Meanwhile, reuse of organic matter and nutrients from sanitation systems is more prevalent worldwide compared to treated wastewater reuse (McConville, 2023).

2.3 Critical challenges in management of water utilities

To provide a comprehensive understanding of the management of water utilities, it is crucial to highlight the major challenges that must be tackled. This section aims to provide an overview of the significant challenges that water utilities encounter in achieving sustainable and effective management. Subsection 2.3.1 outlines the most pressing issues in the current scenario, while subsections 2.3.2, 2.3.3, and 2.3.4 delve into specific challenges related to cost-efficiency, service quality, and asset management, respectively. Finally, subsection 2.3.5 describes the recent approaches developed to address these challenges and highlights the contributions of this thesis.

2.3.1 Pressing issues for sustainable and effective management of water utilities

According to Haasnoot et al. (2011), the future of water management is demanding and sometimes unpredictable due to factors such as climate change, population growth and regulatory pressing issues. These factors create uncertainties that may require transdisciplinary water management strategies, making it essential to identify the most sustainable strategy to adopt (Larsen et al., 2016). Water-related challenges are commonly expressed by professionals using the phrase “too

much, too little, or too polluted.” This succinct statement captures the three primary issues related to water management that pose significant challenges in various contexts (Makarigakis and Jimenez-Cisneros, 2019).

Some urgent concerns currently faced by water utilities are:

- **Climate Change**

Changes in weather patterns and increasing frequency of extreme weather events can impact water availability and quality. Climate change impacts water system management particularly in terms of planning, building, and maintenance. The rise in global temperatures is leading to extreme weather cycles, such as floods and droughts, while sea levels are also increasing, resulting in droughts in some regions that negatively affect water sources. Additionally, the combination of decreasing precipitation rates and increasing extraction rates is putting stress on groundwater supplies. With two-thirds of the world’s mega-cities located in climate-vulnerable regions, water utilities must improve water resource management and infrastructure to provide safe water to residents. Diversifying water sources through sustainable practices like groundwater extraction, water trading, conservation, and the use of recycled or desalinated water is crucial to managing these challenges (Danilenko et al., 2010; Vairavamoorthy et al., 2008; Wilby, 2007).

- **Population Growth**

In just the last century, the global population has grown by approximately four times, and during that same time, human water usage has increased significantly, with agricultural, industrial, and municipal usage growing approximately five, 18, and 10 times, respectively (Nazemi and Madani, 2018). In the years to come, water demand is projected to rise notably due to the global population growth, which could result in water scarcity (Pahl-Wostl et al., 2016). Population growth is concentrated in regions with less abundant water, including Sub-Saharan Africa, the Middle East, and Central Asia. A forecast suggests that by 2050, over 50% of the world population will live in regions that will face water scarcity at least once a year (Ortega-Ballesteros et al., 2021). Sanitation systems are under similar pressure to adapt to the increasing demand. As the demand in the water sector increases, putting pressure on existing water systems, water utilities must find ways to meet this growing demand while ensuring efficient use of resources.

- **Regulatory Compliance**

According to Marques and Pinto (2018), the establishment of regulatory agencies is deemed necessary to protect the welfare of the general public, given the complexity of regulated sectors which make it difficult to ensure their protection. The creation of these agencies is often a part of the reform process with the aim to enhance the accountability of service providers, to establish an independent pricing mechanism, and to utilise regulatory expertise. In order to achieve these goals, autonomous regulatory bodies are endowed with legislative, executive, and judicial powers, allowing them to supervise operators and enforce the necessary

rules. Water utilities must adhere to those various regulations and standards related to water quality, infrastructure, and service provision. Meeting these requirements may entail significant efforts and investments in technology, personnel, and infrastructure.

- **Infrastructure Deterioration**

Many cities and locations with ageing water infrastructure require immediate rehabilitation to meet the demand. Some drinking water transmission systems in Europe and the United States are over a century old, with some pipes dating back to the 19th century. Those laid after World War II typically have a life span of 75 to 100 years, indicating that many are reaching the end of their design life. Due to those conditions, there has been a 27% increase in water main breaks between 2012 and 2018 in the United States, translating to an estimated 250,000 to 300,000 breaks annually or a break every two minutes (Ortega-Ballesteros et al., 2021; ASCE, 2021a). Regarding the wastewater systems, typically their pipes have a lifespan of 50 to 100 years. As collection systems age, they deteriorate, causing groundwater and stormwater to infiltrate the networks through cracks and joints. When collection systems become overwhelmed, sanitary sewer overflows may occur. In North America, approximately 28% of mains are older than 50 years (ASCE, 2021b). Given this scenario, infrastructure renewal and replacement ranking has been considered as the most pressing issue in the sector according to the American Water Works Association Water Industry report for ten consecutive years (ASCE, 2022). The results of decades of little or no pipe replacement or refurbishment are low pressure and high leakage. Low pressure is a symptom of systems not being able to cope with expansion. Leakage alone is estimated to have an equivalent cost of USD 1 billion per year in selected African cities (Rouse, 2013). Global water losses of 126 billion cubic meters per year, worth USD 39 billion, reflect inadequate infrastructure preservation. Saving half of these losses could provide water to 90 million people (Molinos-Senante et al., 2022c).

Effective management is of paramount importance to ensure the efficient and sustainable provision of water services by utilities. Management is faced with various challenges in the current scenario, which arise from the constraints listed above that require immediate attention. Although water utilities face a multitude of challenges (Hasit et al., 2012; EPA, 2017), some of the most significant include achieving cost-efficiency, maintaining high service quality, and effective asset management.

2.3.2 The cost-efficiency challenge

Achieving sustainable water use requires a focus on efficiency due to the high cost of operation and maintenance in water utilities. However, some pricing modes, such as egalitarian pricing, hinder efficiency and negatively impact sustainability. Bithas (2008), in a study that examined several pricing modes, advocates that full-cost prices are necessary to promote social equity in the long run and ensure sustainable water use. Water managers face the challenge of dealing with operational

costs that are sometimes not covered by prices. Among these costs, energy, which is a significant operational cost and increasing over time, plays a crucial role in water supply as all stages of water supply utilities require energy. According to Coelho and Andrade-Campos (2014), the global energy consumption for water distribution is around 7% of the total energy generated. Pumping station operations are the primary consumers of energy in water supply systems, accounting for 50-80% of the total energy consumed. In Europe only, the estimated cost of energy for pumping operations is between 2.9 and 3.9 billion €/year (Reis et al., 2023).

At a broader level concerning cost-efficiency, there are ongoing discussions regarding the most effective structural arrangements for the water supply and wastewater sectors. This discourse includes integrating different scopes, such as water and wastewater or bulk and retail operations, identifying opportunities for economies of scale, and determining management systems and ownership (Abbott and Cohen, 2009; González-Gómez and García-Rubio, 2008).

According to a literature review conducted by Berg and Marques (2011), the question of the optimal size of water utilities is a commonly discussed topic in the water sector. However, the results of the research on this issue are inconclusive and vary depending on the sample and output mix analysed. The existing studies suggest that there are economies of scale up to a certain point, but the implications for optimal utility size are unclear. Consolidation of geographically separate utility operations may reduce managerial overhead costs, but coordination costs may rise, making decisions slower with larger bureaucracies. Thus, determining the optimal size of utility operators cannot be generalised, and location-specific factors are more important when evaluating consolidation or decentralisation.

More research is needed to assess efficiency gains associated with economies of scope, such as joint provision of drinking water supply with sanitation, or other activities like piped gas, electricity or urban waste. Vertical integration within water and sanitation utilities, i.e. providing wholesale and retail services simultaneously, can result in some advantages for drinking water supply. Economies of density, both in production and customer density, have been identified in the literature.

Berg and Marques (2011) also discuss the issue of ownership in water utilities and identified lack of consensus in the literature. While some economic theories suggest that the private sector performs better, a review of 47 studies found that 18 concluded that private utilities are more efficient, 12 found public utilities to be more efficient, and 17 were inconclusive. There is some agreement that private utilities tend to have higher labour productivity but also higher capital expenses. Historically, the public sector has tended to under invest in infrastructure and has lower labour productivity.

2.3.3 The quality service challenge

Ensuring safe drinking water and reliable supply and sanitation services is a critical aspect of water utility management. Water utilities must invest in water and wastewater treatment technologies and establish effective water quality monitoring programs to safeguard public health. It involves

maintaining water quality, preventing contamination, managing water resources, and ensuring adequate storage and distribution systems. Making sure that the drinking water supplied by public systems is of good quality is a crucial aspect of public health policies (Roeger and Tavares, 2018).

Moreover, the quality of utilities' services is not limited to the physical quality of water and wastewater. It also involves ensuring that these services are accessible and reliable. A frequently used measure of utility performance is the uninterrupted provision of services, with a goal to provide available service 24 hours a day, 7 days a week (known as continuous supply), being regarded as the ideal standard (Rawas et al., 2020). As stated by Kumar et al. (2013), assuring reliable and safe water services is a highly intricate task, particularly in developing countries where piped water supply is irregular, with low pressure, high leak rates, and poor maintenance practices along the supply chain, leading to a significant gap between supply and demand. This inadequate water supply is also unequally distributed among different consumer categories. Despite being the most crucial factor in public health, a clean water supply is jeopardised by source contamination, deteriorating infrastructure of water distribution systems, leakages, cross-contamination, and unsanitary practices. Diarrhea is the most frequent cause of illness and death globally, with 88% of these deaths attributable to a lack of access to safe drinking water and adequate hygiene facilities.

Addressing these complex issues requires the implementation of comprehensive strategies that encompass infrastructure investment, improved maintenance practices, and equitable distribution of water resources. By prioritising the quality of services provided, water utilities play a crucial role in advancing human society. Their efforts contribute to ensuring universal access to clean and reliable water, a fundamental necessity for the well-being and prosperity of all individuals.

2.3.4 The asset management challenge

Effective management is essential for maintaining the infrastructure and assets required for the provision of water services. Water utilities are asset-intensive systems, and asset management practices are vital for ensuring their long-term sustainability. This involves developing and implementing asset management plans to optimise the use of existing infrastructure, identify maintenance and repair needs, and plan for future investments. Regular maintenance, repair, and replacement of ageing assets are needed to ensure an uninterrupted water supply. Many water systems were built decades ago and have reached the end of their design life. As a result, water utilities must invest in upgrading and replacing ageing infrastructure to ensure reliable and efficient service provision. The neglect of infrastructure preservation, especially water mains and sewers, is a prevalent problem in many developed regions. These systems have long lifetimes and are difficult to inspect, resulting in significant service disruptions before any visible deterioration occurs. Water charges have been too low to save enough money for necessary replacements. While system managers acknowledge the need for refurbishment, the political difficulty of increased government subsidies or charges has hindered the implementation of renovation programmes. Only in the United States, the investment in water infrastructure is estimated in USD 1.7 trillion up to 2050. There is a similar backlog of investment in existing systems in developing countries. Many of the systems were constructed in colonial times, and, although the cities have grown since that time,

water supply systems have not been able to keep pace with urban development (Molinos-Senante et al., 2022c).

The importance of enhancing the resilience of infrastructure, particularly in the context of extreme weather events, is steadily increasing. According to Hallegatte et al. (2019), investing \$1 in enhancing the resilience of critical infrastructure can yield \$4 in return. Hence, there is a need for appropriate actions to be taken towards water-related assets, considering their entire lifecycle and future generations. This involves developing the capability to: (1) withstand the initial impact of hazardous events; (2) minimise the adverse effects of such events; (3) quickly adapt to the resulting changes; and (4) enhance water-related assets to enhance preparedness against forthcoming threats and variations (Rezvani et al., 2022).

A common issue with water infrastructure is the transportation and protection of treated water through the distribution system. Many current systems have poorly maintained and inadequately sized infrastructure, resulting in low or no pressure in the network, intermittent water supply, and contamination. Some systems have oversized pipes and pumps, leading to higher costs and poorer water quality due to excess capacity. This is often due to outdated sizing or declining water demands. Furthermore, innovative methods for detecting leaks such as analysing water usage data with advanced metering, pressure loggers, data-mining and inspection with traditional acoustic methods, thermal imaging, robotic inspection and pressure management can assist water suppliers in identifying distribution system issues and managing water losses. Other than that, repairing and replacing underground water infrastructure is costly and complicated, as it may affect other properties, traffic, and buildings. Various techniques are required to repair the different types of pipes in a distribution system, making the process even more challenging. Therefore, there is an urgent need for innovations to efficiently reduce and control water loss and extend the life of pipes (Milman et al., 2021).

2.3.5 Contributions to address the challenges

In recent years, the scientific community has dedicated considerable efforts towards finding solutions and alternatives to help utilities overcome the challenges they face in managing and operating their systems. According to a review by Ortega-Ballesteros et al. (2021), there has been a significant increase in awareness among researchers in this field, leading to a growing number of scientific publications on this topic since the start of the current century.

Moreover, in the past twenty years, there has been a shift in thinking about urban water management, which reflects a larger cultural shift towards valuing natural processes and systems, as opposed to relying solely on technological and mechanistic solutions. This new paradigm represents a departure from the traditional approach to managing water in cities. New management frameworks have been developed to tackle current challenges. According to Franco-Torres et al. (2021), different scholars have launched novel ideas on frameworks for water management, including new styles of governance, circular use of resources or modular ecosystem-based infrastructures.

The International Organisation for Standardisation (ISO) has been also promoting actions aimed at improving the management of water systems. In 2001, the ISO technical committee ISO/TC 224 was launched to develop guidelines for the activities related to water supply and wastewater systems. Six years later, ISO/TC 224 released three new ISO standards addressing water services: ISO 24510 (ISO, 2007a) focusing on the service provided to users of both water and wastewater systems, ISO 24511 (ISO, 2007b) dealing with management practices of wastewater utilities and ISO 24512 (ISO, 2007c) addressing management practices of drinking water utilities.

The ISO/TC 224 Standards provide a framework to improve the governance of water services and promote quality and efficiency. They facilitate dialogue among stakeholders such as consumers, water authorities, utilities, research departments, and laboratories. The standards enable a mutual understanding of responsibilities and tasks and provide methods and tools to define objectives and specifications and assess performance. They can be applied voluntarily in both industrialised and developing countries, and in any setting, whether the utility operator is public or private. The ISO/TC 224 standards address several key areas, including defining common terminology for stakeholders, clarifying consumer expectations and service elements, developing optimised management actions, proposing measurable quality criteria and performance indicators, and enabling local-scale comparisons of observed results with targets set by water authorities. These standards promote benchmarking among water utilities and can help protect the environment while meeting the needs of water users (ISO, 2004).

ISO has taken another important step in promoting effective asset management by publishing a family of standards in 2014. Comprising of ISO 55000, ISO 55001, and ISO 55002, this framework provides a comprehensive approach for managing any type of assets, whether it be railway sleepers, brand reputation, or telecommunications networks (ISO, 2014a,b). ISO 55001, specifically, lays out the requirements for effective asset management and creates a system designed to optimise performance, mitigate risks, and minimise costs throughout the entire asset lifecycle. Organisations can seek certification for compliance with this standard, similar to other ISO standards like ISO 9001 for quality management systems or ISO 14001 for environmental management systems, upon successful implementation of the requirements. It is worth noting that these management systems have a common foundation in the Deming cycle (PDCA: Plan-Do-Check-Act), originating in the field of quality management. According to Sousa and Meireles (2022), the PDCA cycle serves as the inspiration and basis for the sequence of Leadership, Planning, Support, Operation, Performance, and Improvement, which is shared among all ISO management standards.

The United Nations has recognised the crucial role of effective water management in achieving sustainable development. To this end, UNESCO, the scientific arm of the United Nations, launched the International Hydrological Programme (IHP) to raise awareness among communities and decision-makers about the significance of water-related issues. Since 1975, IHP has developed a comprehensive set of 17 worldwide initiatives aimed at creating scientific and technological tools for evidence-based decision-making, promoting international cooperation through networking, en-

hancing the science-policy interface, and focusing on education and training for building human capital at the local, regional, and global levels (Makarigakis and Jimenez-Cisneros, 2019).

The World Bank Group is actively supporting the latest advancements in water management practices. In 2014, the Bank established the Water Global Practice, which serves as an integrated platform for financing, expertise, and implementation efforts. By combining the Bank's global knowledge with local investments, this initiative generates greater capacity for implementing transformative solutions that promote sustainable growth in countries. As part of this effort, the Bank launched the Utility of the Future (UoF) programme, which offers a novel approach to planning and implementing reforms aimed at making water utilities more sustainable (Lombana Cordoba et al., 2022).

The European Union (EU) recognises that water has value beyond its usefulness as a resource for humans, and has taken steps to establish policies for the preservation of aquatic ecosystems as natural capital. The Water Framework Directive (2000/60/EC) was a significant milestone in this direction, establishing a new approach to water management that considers its role in supporting ecosystems. The EU's more recent action plan for sustainability, the Biodiversity 2030 strategy, recognises the importance of restoring and preserving nature, including water resources. As part of this plan, measures such as reducing water pollution, promoting efficient and circular water use, raising awareness of the natural capital provided by biodiversity and ecosystem services, and adapting to climate change, will help to protect and restore ecosystems. It is important for the global community to make a collective effort to protect water resources in order to achieve sustainable growth (European Commission, 2020).

2.4 Emerging trends in water utility management

This section presents some latest trends in water utility management. With the water sector rapidly evolving, it is crucial to remain up-to-date with emerging trends that are being adopted to address the previously discussed challenges in water utility management. Some of those trends include:

- **Digitalisation**

The integration of advanced Industry 4.0 technologies such as artificial intelligence, the Internet of Things (IoT), and Big Data can significantly improve the performance and efficiency of the water sector. The industry is also witnessing the emergence of innovative technologies like smart water systems, which utilise real-time data analysis and sensors to monitor and manage water distribution networks, resulting in increased efficiency and reduced waste. Furthermore, the implementation of artificial intelligence and machine learning algorithms can optimise water treatment processes and predict potential system failures (Silva, 2022).

To achieve a “Smart City” approach to water resource management, infrastructure monitoring, data collection, and analysis, and decision support systems integrating IoT, Big Data, and blockchain technologies are necessary. Data analysis and the use of computational

intelligence techniques are critical in this approach for monitoring water consumption, predicting pipe failures, and forecasting water demand. Decision support systems must incorporate multiple tools to address various issues such as ensuring water quality, availability, and infrastructure maintenance. Anomaly detection tools generate notifications and alarms to signal abnormalities such as water contamination, distribution network malfunctions, or cyber attacks on water treatment facilities. Water demand models and simulation tools are employed to evaluate the effect of new rules on reducing water consumption or forecasting water demand for residential areas under development. Infrastructure maintenance planning tools should include pipe failure predictors to reduce the costs associated with unexpected pipe breaks.

Future developments should focus on integrating different types of data, creating decision support systems, and standardising methodologies to create large-scale systems for water infrastructure management (Hangan et al., 2022).

- Increased focus on sustainability and circular economy

The increasing concern about water scarcity in various areas has prompted utilities to explore methods of minimising water waste and encouraging water conservation. This encompasses the promotion of water reuse, the collection of rainwater, and other unconventional water sources. Moreover, utilities are adopting more sustainable practices in their day-to-day operations, which entails lowering energy consumption and greenhouse gas emissions (Silva, 2022).

In the study performed by Larsen et al. (2016), various strategies to improve water productivity in the Urban Water Cycle are discussed, including reducing wastewater, reusing lower-quality water, and regenerating high-quality water from used water. Globally, only 1.7% of water supply is currently reused, primarily for irrigation purposes. The authors also suggest source separation of waste as a promising trend, which can be implemented at both the household and device level, such as using a recycling shower that recirculates shower water in real time. The practice of separating greywater not only conserves water but also can recover energy and nutrients. Examples of successful source separation initiatives include China's 40 million domestic biogas reactors and the almost 100,000 urine-diverting dry toilets in peri-urban areas of eThekweni, South Africa.

- Infrastructure risk management

Regulatory authorities have shifted towards promoting an integrated risk management approach to minimise the risk of water system infrastructure failures. This involves implementing several protective barriers such as source water protection, redundant treatment designs, and continuous monitoring of distribution systems. The adoption of the World Health Organisation's Water Safety Plans (WSPs) by over 90 countries is an example of this approach. The WSPs require the proactive management of all water system assets from source water to tap, resulting in a decrease in diarrheal diseases, improved communication

between water system stakeholders, and better overall management of water system assets. However, implementing risk management approaches necessitates institutional and cultural change. Water suppliers need to undertake an honest evaluation of their current systems and practices proactively instead of reacting to risks to be effective (Milman et al., 2021).

- Capacity-building efforts

Historically, ownership has been considered the key factor in improving the management of water utilities. However, the privatisation movement in the 1980s resulted in inconsistent outcomes, with some privatised systems performing no better or even worse than public ones. In the 1990s and 2000s, interest shifted towards public-private partnerships or corporatisation initiatives, where state-owned systems were kept under public control but managed as independent entities. Despite a variety of different structures appearing, success rates were inconclusive.

It has now been recognised that good management of water utilities is not solely dependent on ownership, and there is a need to look beyond this factor to understand the reasons behind the success or failure of these systems. Recently, attention has shifted towards the institutional and regulatory environments in which these utilities operate, with “governance” being a key point of discussion.

The focus is on creating an environment that enables water systems to operate effectively, which includes ensuring accountability and autonomy, providing oversight before new systems are developed, and designing appropriate incentives for water system management. Additionally, there is a focus on improving the internal capacity and culture within water systems. Studies have shown that successful water suppliers have a strong knowledge base, human and organisational capacities, a willingness to learn, a focus on customers and business, effective measurement practices, and a culture of continuous improvement.

The emphasis on improving water management through the enabling environment is expected to continue, with a specific focus on enhancing capacity-building efforts. This is already happening with support from national, sub-national governments, and international donors who are investing resources in water system management. Key activities include training, creating and promoting self-assessment tools, providing guidance and best practices, and providing financial support to water suppliers to improve their capacity. Capacity-building efforts will also likely continue to facilitate the development of water system partnerships, which can help build capacity through resource leveraging, taking advantage of economies of scale, and filling gaps in specific operational or management responsibilities such as billing, water quality testing, or shared operators (Milman et al., 2021).

Despite a century of efforts to develop successful paradigms, management of piped water systems remains a significant challenge. Improving the institutional and regulatory environment and promoting capacity-building efforts and partnerships are key to addressing the challenges associated with managing those systems.

2.5 Conclusion

This chapter has highlighted the critical role of management practices in the water utilities industry and underscored its importance as a relevant area for research and practical application. The chapter detailed the challenges that water utilities face, including the need to pursue cost-efficiency, maintain high service quality, and manage assets effectively.

This thesis aims to play a role in supporting the existing management frameworks by introducing specific decision-making tools designed to address the current challenges faced by water utilities. The tools intend to guide the development of effective strategies to overcome the aforementioned challenges. Chapter 4 is dedicated to addressing the cost-efficiency challenge, while chapter 5 focuses on the quality of services. Chapters 6, 7, and 8 are dedicated to deal with issues related to asset management.

Effective management practices are strongly required for the efficient, sustainable, and reliable provision of water services by utilities. As previously noted, those practices have been vastly discussed worldwide. By adopting the mentioned best practices at a broader level, utilities can ensure the long-term viability of water resources and maintain reliable access to safe water for their customers.

Decision support tools for water utility management

Efficient decision-making is essential for water utilities to address the sector's significant challenges and ensure optimal resource utilisation. Decision support tools aid this process by enabling water utility managers to analyse data, assess performance and optimise operations. This chapter offers a comprehensive introduction to the decision support tools that will be explored in greater detail throughout the thesis, emphasising their critical role in addressing the challenges faced by water utilities. The decision support tools developed in this thesis rely on mathematical programming models based on non-parametric frontier methods and optimisation. The field of mathematical programming decision models is vast and involves multiple disciplines. This chapter presents an overview of these techniques and highlights their applications in water utility management. These tools provide a data-driven and objective basis for management decisions. The research outcomes will contribute to the literature on water system management and provide practical tools for decision-makers in the sector to enhance the efficiency and effectiveness of water system management.

3.1 Introduction

According to Wong-Parodi et al. (2020), “decision support tools are the array of computer-based tools developed to assist sound decision-making”. They can be particularly useful in scenarios where the volume of data is too large for an individual to rely solely on their intuition for decision-making, especially when making high-impact choices. Those tools or systems can bridge the gap of human cognitive limitations by bringing together diverse sources of information, enabling access to pertinent knowledge, and streamlining the decision-making process. By leveraging their use appropriately, it's possible to enhance productivity, efficiency, and effectiveness, ultimately leading to optimal decision-making (Zhang et al., 2014).

The expressions “decision support tool (DST)” and “decision support system (DSS)” have been used indistinctly in the literature, although for some scholars, the term DSS is more applied to broad “computer technology solutions” comprising “sophisticated database management capabilities with access to internal and external data, information and knowledge, powerful modelling functions accessed by a model management system, and powerful yet simple user interface designs that enable interactive queries, reporting and graphing functions” (Shim et al., 2002). Some authors have a narrower view of DSS, considering it more as a supporting tool rather than a complete system. As mentioned by Power (1997), operation researchers consider optimisation and simulation models as true “decision support systems”, allowing the term DSS to encompass a

wide variety of systems, tools, and technologies. It's worth noting that the definitions and usage of both terms DSS and DST vary based on the author's viewpoint, and the terms remain applicable to different types of information systems that facilitate decision-making (Mir and Quadri, 2009).

In this thesis, we opt to use the term “decision support tools” (DSTs) as computer-based tools that support decision-making processes by presenting information and analysis in an organised and systematic way. DSTs can help water utility managers to make more informed decisions by providing a range of options, outcomes, and potential risks associated with each decision.

In recent years, the availability of massive amounts of data has drastically changed the way management decisions are made. Decision-makers now have access to more accurate and reliable information, thanks to the increasing use of data-driven approaches. One such approach is known as *analytics* (or *business analytics*), which Hillier and Lieberman (2014) define as “the scientific process of transforming data into insight for making better decisions”. The rise of analytics represented a significant shift in the way that management decisions are made, as DSTs became more data-driven and agile in the decision-making process.

There are several types of DSTs available for water utility management, including simulation models (Jeppsson and Hellström, 2002; Cetinkaya et al., 2008; El-Gafy and El-Ganzori, 2012; Shao et al., 2014), optimisation models (Makropoulos and Butler, 2004; Mala-Jetmarova et al., 2017, 2018), multi-criteria methods (Mutikanga et al., 2011; Choi and Park, 2001; Kumari and Wijesekera, 2021; Hajkowicz and Higgins, 2008; Zolghadr-Asli et al., 2021), and data-driven models (Singh and Mishra, 2021; Di et al., 2019; Myrans et al., 2016).

Simulation models are employed to replicate the behavior of water systems under different circumstances, such as alterations in water demand, water quality, or climate. Optimisation models are utilised to identify the most favourable solution to a problem, given a set of constraints and objectives. Multi-criteria tools are implemented to make decisions when there are various factors to consider, conflicting criteria and different stakeholder interests. Data-driven models employ statistical and machine learning techniques to detect patterns and relationships in data, which can be used to make predictions or classify data.

Bello et al. (2019) present a detailed review of management problems faced by water utilities and the mathematical decision models used to address those problems. Many of those tools are used to explain and simulate the behaviour or responses of water networks, and estimate the conditions of the networks under particular operating and loading conditions. Among them, there are the various types of hydraulic models to determine flow conditions, water quality models, demand forecasting tools and water leakage models.

With the advent of the fourth industrial revolution, urban water management has evolved into “smart” as a way to achieve water sustainability. “Smart water management” utilises information, communication technology and real-time data to tackle water management challenges by integrating digital solutions into urban, regional, and national strategies. Smart technologies, such as sensors and IoT (Internet of Things) networks, cloud-based technologies, algorithms, and big data analytics, have been used to achieve water security in urban landscapes and industrial facilities (Kumar et al., 2013). Automation in complex urban water systems is mainly based on receiving

feedback from sensors and using computer algorithms to analyse signals and propose specific actions. The adoption of digitalisation improves efficiency, flexibility, and provides novel services to society at reduced costs. The European Union has been funding research projects in this direction, and the water market has been shifting towards digitalised business models. Smart technologies have facilitated the real-time monitoring, optimisation, and forecasting of freshwater consumption and pollution, and they serve as decision support tools (Aivazidou et al., 2021; Oberascher et al., 2022).

By using DSTs, water utilities can make more informed decisions that take into account a range of factors, such as cost, efficiency, and environmental impact. In addition to supporting decision-making, DSTs can also help to improve communication and collaboration among stakeholders. By presenting information in a clear and accessible way, DSTs can help to facilitate discussions and negotiations among different groups with competing interests.

Two specific types of DSTs are employed in this thesis: optimisation-based tools and frontier methods. An optimisation model, as defined by Mala-Jetmarova et al. (2018), is a mathematical representation of an optimisation problem that includes objective functions, constraints, and decision variables. While frontier methods like Data Envelopment Analysis can also be based on optimisation models, they are typically considered separate sets of tools. As such, in this thesis, we have chosen to treat them as distinct from each other.

The remainder of this chapter will discuss the general concepts and the water management applications of the two types of DSTs used in the thesis. Section 3.2 addresses optimisation and Section 3.3 covers frontiers methods. A brief conclusion is presented in Section 3.4.

3.2 Optimisation models

This section outlines the general concepts of optimisation techniques in subsection 3.2.1 and their usage in water utility management in subsection 3.2.2.

3.2.1 Overview of optimisation models

Although the concept of *analytics* emerged as the world entered the era of “big data”, it has increasingly been integrated into an existing approach called *operations research*. The principles of operations research have been used for decades to solve organisational problems using analytical and numerical methods. They are generally credited with having been introduced into military services during World War II, when there was a need to allocate scarce resources efficiently (Hillier and Lieberman, 2014). As businesses became more complex in the post-war period and computational resources became available, these ideas rapidly spread throughout management practices.

The essence of operations research, also named as *management science*, is the model-building approach, which involves the use of mathematical models to capture the significant features of the decision under consideration. Models are simplified representations of the real world that must be easy to understand and incorporate all relevant elements of the decision environment to be useful in supporting management decisions. Managers should formulate the basic questions to be

addressed by the model and then interpret the model's results in light of their own experience and intuition, recognising the model's limitations (Bradley et al., 1977).

Models that aim to find optimal solutions, known as *optimisation models*, are fundamental to operations research and often rely on mathematical programming techniques. These models identify the maximum or minimum values of numbers, functions, or systems (Kiranyaz et al., 2013). By leveraging the power of mathematics, optimisation models help researchers and practitioners make better decisions, allocate resources efficiently, and solve complex problems in various fields.

A general optimisation model can be illustrated as 3.1, as noted by Kim et al. (2018).

$$\begin{aligned}
 &\text{Optimise} \quad z = f(x) \\
 &\text{subject to} \quad g(x) \in s_1 \\
 &\quad \quad \quad x \in s_2
 \end{aligned} \tag{3.1}$$

The *decision variable*, denoted by x in model 3.1, is selected to optimise a certain objective. This objective is expressed mathematically as $z = f(x)$, where $f(x)$ is commonly referred to as the *objective function*. The objective function shows how different choices of x impact the decision maker's satisfaction in terms of the objective, and can be either *maximised* or *minimised*. However, in choosing the appropriate value for x , a set of *constraints* must be followed to ensure that x behaves in a certain way. These constraints are reflected in the formulation above by the requirements that: (i) $g(x)$ must fall into s_1 , and (ii) the variable must belong to s_2 .

As outlined by Datta et al. (2018), optimisation techniques can be categorised in various ways, based on factors such as the presence of constraints, the number of objectives, and the nature of the objective function and constraints. Linear programming is used when the objective function and constraints are linear, while nonlinear programming is used when the objective function and/or constraints are nonlinear. In cases where there are multiple conflicting objectives, multi-objective optimisation is used to find a set of optimum non-dominated solutions.

An optimisation problem where all variables can only be integers is known as an *all-integer programming problem*. If the variables are restricted to discrete values, it's called a *discrete programming problem*. When some variables can only be integers, the problem is a *mixed-integer programming problem (MILP)*. If the optimisation problem only allows design variables to be either 0 or 1, it's called a *binary programming problem*. To solve all-integer and mixed-integer linear programming problems, specific techniques such as Gomory's cutting plane algorithm and Land and Doig's branch-and-bound algorithm must be employed (Rao, 2009).

According to Bradley et al. (1977), one of the typical applications of all-integer and mixed-integer programming models are capital-budgeting problems. These problems involve selecting the most suitable option among various potential investments, such as plant locations, capital equipment configurations, or research-and-development projects. In many cases, it doesn't make

sense to make partial investments in these activities, and the problem can be solved as a “go-no-go” integer program. This means that the decision variables, denoted as x_j , can only take on values of 0 or 1, indicating whether the j^{th} investment is rejected or accepted.

Offline optimisation is used when time is not a critical factor and users are willing to wait for optimal or close-to-optimal results. In contrast, online optimisation is used when the job needs to be solved within seconds or milliseconds, and the focus of the algorithm is on speed (Datta et al., 2018).

As stated by Sörensen (2015), optimisation algorithms can be broadly classified into two categories: exact algorithms and heuristics. The key distinction lies in the fact that exact algorithms are specifically designed to guarantee finding the optimal solution within a finite time frame. However, the use of exact algorithms is often limited due to the impracticality of exhaustive search in complex problems. This limitation has led to the development of heuristic techniques, which aim to find good solutions efficiently, even if they are not guaranteed to be optimal. In recent years, there has been a paradigm shift in perceiving heuristics as a viable field of research, alongside exact methods. This shift has coincided with the emergence of a new concept known as metaheuristics. Metaheuristics provide a cohesive framework comprising ideas, concepts, and operators for designing effective heuristic optimisation algorithms. They are advanced strategies for exploring search spaces using various methods, striking a balance between *diversification*, which involves wide exploration of the search space, and *intensification*, which entails leveraging accumulated search experience for exploitation (Blum and Roli, 2003).

Nowadays, metaheuristics techniques are widely employed in the field of optimisation, as they are capable of dealing with complex design problems and generating high-quality solutions in a reasonable amount of time. Evolutionary algorithms are a type of metaheuristic technique that falls under the evolutionary computation group. This group includes genetic algorithms, genetic programming, evolutionary strategies, and differential evolution, among others. Evolutionary algorithms are inspired by the process of natural selection and work by generating a population of candidate solutions that are then evolved through a process of selection, reproduction, and mutation. This process continues until a satisfactory solution is found or a stopping criterion is met. Swarm intelligence techniques, such as particle swarm optimisation and ant colony optimisation, are another group of metaheuristic techniques that are inspired by collective behaviour in nature.

As research and innovation progress in the field of optimisation, these techniques continue to evolve, providing novel insights and methodologies for addressing complex challenges.

3.2.2 The use of optimisation models as decision support tools in water utility management

Optimisation models are versatile tools for addressing management problems in water systems. They are able to minimise costs, reduce discrepancies between measured and simulated values, or maximise performance indices. Optimisation techniques search for the best possible solution among all available options. In these models, objective functions for water network problems are typically limited by constraints that represent physical mass and conservation laws, minimum

pressure requirements at demand nodes, and other significant inequality or equality restrictions, depending on the problem at hand. Decision variables can take the form of continuous or discrete values representing a set of feasible solutions to optimisation problems (Bello et al., 2019).

The design and operation planning of water systems have a long history of using optimisation methods. This practice dates back to the late 19th century, with the first examples identified by Mala-Jetmarova et al. (2015). Over the years, the development of computing power has further boosted the research in this area. As a result, there has been a rapid growth in the development and use of system analysis methods related to water systems. Mala-Jetmarova et al. (2017, 2018) reported that more than 300 journal papers have been published in the last three decades alone on the topics of water systems design and operational optimisation.

Numerous approaches have been proposed and extensively discussed to solve optimisation problems related to water distribution networks, including enumeration, linear programming, non-linear programming, dynamic programming, integer programming, stochastic or meta-heuristics, and hybrid optimisation techniques (Balekelayi and Tesfamariam, 2017). Among these, the meta-heuristics technique is favoured due to its ability to find near-optimal solutions within a reasonable amount of time. Linear programming and genetic algorithms are examples of optimisation techniques that can be used to identify optimal solutions to problems, given a set of constraints and objectives. These methods can optimise water utility operations by scheduling maintenance activities, allocating resources, and setting prices (Bello et al., 2019; Savić et al., 2018). Several factors must be considered in selecting an appropriate optimisation technique. These factors may include the allowed computation time, the size of the case study, and the desired quality of results. It's important to note that there is no one-size-fits-all algorithm that can be applied to all water optimisation problems. Therefore, careful consideration of the specific problem at hand is essential in choosing the most suitable optimisation technique (Balekelayi and Tesfamariam, 2017).

In a survey about optimisation problems in water distribution networks, Ruiz-Vanoye et al. (2018) highlight the relevant applications of optimisation techniques to solve problems related to those systems. Those applications include managing water quality, improving chemical transport, optimising repair costs and selecting piping, pumps and valves. Horne et al. (2016) discuss the use of optimisation in environmental water decisions. They note that over half of the examined literature focused on evolutionary techniques. The authors also emphasise the importance of specialised knowledge and expertise in utilising these tools effectively. However, they point out that stakeholders have been largely excluded from the model development process in this field, indicating a need for greater stakeholder involvement.

Among other applications, the use of optimisation for asset management practices is discussed by Bello et al. (2019). Regarding this matter, it is important to intensify research efforts in developing a widely-accepted rehabilitation prioritisation model with performance metrics, specifically for real systems operating under budget constraints. Additionally, there is a need to improve decision support systems for planning rehabilitation and optimising pipeline maintenance, making them more user-friendly and flexible. To achieve this, a novel asset management approach that incorporates accurate predictions of pipe failure rates, service lifetimes, and appropriate cost

structures and discount rates for pipeline failures should be proposed.

This thesis employs optimisation methods, specifically MILP and evolutionary algorithms, to tackle the task of defining a portfolio of investment projects in the water utility sector. Chapter 8 provides a detailed description of the techniques utilised.

3.3 Frontier methods

In this section, an overview and key concepts of frontier methods are presented in subsection 3.3.1, along with their applications in water utility management, which are discussed in detail in subsection 3.3.2.

3.3.1 Overview of frontier methods

Frontier methods are a set of quantitative techniques used to estimate an efficiency frontier of a set of entities, known as decision-making units (DMUs). To measure the technical or economic efficiency of DMUs, such as schools, hospitals, utilities, or countries, input and output combinations to these entities need to be defined. These inputs and outputs are used to create the best-practice frontier, which includes the most efficient DMUs.

In that sense, frontier methods are used to execute relative performance evaluations, which are commonly referred to as benchmarking. According to Bogetoft and Otto (2010), this concept involves making a comparison between entities (DMUs) that convert similar resources into comparable products or services.

As decision support tools, the frontier methods facilitate *learning* and improve *coordination* among the units under assessment. Taking the learning approach, the goal is to acquire new insights. When a relative comparison is undertaken, the units find out how well they are doing and which are the other units they can learn from. For instance, the breakdown of overall efficiency into various components can identify specific ways to improve efficiency, such as adjusting the scale of operations or allocating resources. Further enhancements of the learning perspective allow units to customise their benchmarking exercises by choosing comparison peers, objectives, and aspirations. Regarding the coordination perspective, the objective of benchmarking may be to address the allocation of tasks and potentially restructure units. Coordination is a crucial aspect of traditional micro-economic theory and management science that ensures the synchronisation of various departments and groups to work together in harmony. In order to achieve optimal cost and performance, benchmarks, tournaments, and bidding schemes are widely used to coordinate operations in firms and industries. For instance, a bank's headquarters may benchmark operations to motivate local managers and allocate resources and staff according to their performance (Bogetoft and Otto, 2010). Without knowledge of an organisation's past or present performance, managers cannot set realistic targets for future performance. Metric benchmarking helps managers and regulators by quantifying the relative performance of organisations, allowing them to design policies and incentive programs to improve performance (Berg and Padowski, 2010).

In frontier methods, the best-practice or efficient frontier represents the maximum output that can be produced using the available inputs, given the fixed technology and other resources. Production functions can be used as mathematical formulations of the relationship between the maximum level of production outputs and inputs. According to Førsund et al. (1980), the word *frontier* may be applied also to production functions since the function establishes a limit to the possible set of observations. For example, a point can be located below the production frontier meaning that it is producing less than the maximum possible output, but no points can lie above the production frontier. Deviations from this frontier can be used to determine the technical or economic efficiency of other DMUs (Kalb, 2010).

In the definition of technical efficiency provided by Koopmans (1951), a producer can be considered technically efficient if producing an additional output requires using more input(s) or producing less of another output, or if using less of one input requires using more of another input or producing less of one output. Hence, a technically inefficient producer could produce the same amount of outputs with a lesser quantity of at least one input, or could generate more of at least one output using the same amount of inputs. Debreu (1951) and Farrell (1957) developed a method for assessing technical efficiency, which involves two alternatives: input-oriented and output-oriented. In the orientation to inputs, the technical efficiency measure is described as the maximum feasible radial reduction in all inputs, while maintaining the same output level, expressed as one minus that reduction. On the other hand, in the output-orientation, their measure is defined as the maximum radial expansion in all outputs that can be achieved while keeping the same input level. In both cases, a value of one represents technical efficiency, since no radial adjustment is feasible. Any value other than one shows the degree of technical inefficiency (Fried et al., 2008).

As noted by Kalb (2010), several problems may arise when generating the best practice frontier from a data set of DMUs and identifying the extent to which deviations from the best practice frontier are due to real inefficiencies or measurement errors. *Non-parametric* and *parametric* methods have been used to estimate best-practice frontiers and *deterministic* and *stochastic* approaches have been identified regarding the deviations from these frontiers.

The use of parametric and non-parametric frontier methods evolved in parallel, leading to the development of two distinct streams of research and generating intense debate among scholars (Asmare and Begashaw, 2018). The two strategies differ in that the parametric approach requires defining a functional form of the efficient frontier, while non-parametric methods estimate the frontier empirically using sample observations. The need for a defined functional form is the main disadvantage of parametric methods, while the deterministic nature of the non-parametric methods represents their primary drawback (Murillo-Zamorano, 2004).

Non-parametric approaches, such as Data Envelopment Analysis (DEA), are primarily deterministic and use mathematical programming techniques, assuming no random noise in the data. Thus, deviations from the frontier are interpreted solely as inefficiency. On the other hand, parametric methods can be either deterministic or stochastic. Stochastic parametric approaches employ statistical techniques to estimate the production frontier, enabling the differentiation between non-normal residuals indicating inefficiency and normal residuals representing noise or measurement

error in the data (Murillo-Zamorano, 2004).

Among the parametric techniques, SFA is the most commonly used method and was independently introduced by Aigner et al. (1977) and Meeusen and van Den Broeck (1977). In SFA, an econometric model is used to construct the efficiency frontier, and deviations from the frontier are regarded as a combination of random error and inefficiency. The error term is modelled as a two-sided distribution, typically with a normal distribution with a zero mean, and the inefficiency term is assumed to be non-negative and follows a one-sided distribution (Asmare and Begashaw, 2018).

Among the non-parametric frontier methods, DEA is the most popular approach. It was originally introduced by Charnes et al. (1978) as a way to address the frontier estimation proposed by Farrell (1957) using mathematical programming models with multiple inputs and outputs.

DEA and SFA are widely regarded as the most important methods for evaluating the efficiency of individual and organisational performance. A bibliometric analysis conducted by Lampe and Hilgers (2015) tracked the evolution of these methods and identified a constant increase in the number of publications related to both approaches between 1978 and 2012. DEA has become a standard technique in Operations Research, while SFA is mainly studied in Economic research. The study also discusses the main differences between the two techniques, which are summarised in Table 3.1.

Table 3.1: Distinction between DEA and SFA - Adapted from Lampe and Hilgers (2015)

	Data Envelopment Analysis (DEA)	Stochastic Frontier Analysis (SFA)
Elements	Multi inputs and outputs	Single input (output) and multiple output (input)
Algorithm	Linear programming	Regressions (typically using maximum likelihood estimation)
Consideration of noise	Noise is included in the efficiency score rather than accounted for directly (deterministic model)	Explicitly accommodates noise (stochastic model)
Functional form/ input-output relation	Not specified	Functional form is specified (e.g. linear, semi-log, double-log)
Factor weights	Individual factor weights for each unit (non-parametric)	No individual factor weights in the basic model (parametric)

Recent advancements in DEA and SFA have addressed certain comparative limitations between the two techniques, as shown in Table 3.1, with new methods in SFA now allowing for multiple inputs and outputs, and DEA incorporating robust techniques to attenuate its deterministic nature.

This thesis adheres to the non-parametric research stream and focuses on assessing efficiency using DEA-based models. Furthermore, the thesis explores the application of composite indicators derived from DEA, as introduced by Cherchye et al. (2007). Directional Distance Functions (DDF) are employed in the developed models, along with robust and conditional techniques.

3.3.2 Use of frontier methods as decision support tools in water utility managing

Benchmarking practices in the water sector are commonly employed to assess the performance of a water utility by comparing it with other utilities or industry benchmarks. By conducting benchmarking exercises, water utilities can identify areas where they are underperforming and implement strategies to improve their efficiency and decrease costs (Sala-Garrido et al., 2023). Literature reviews covering benchmarking methods were issued by Berg and Marques (2011) and Goh and See (2021).

Frontier techniques have been widely used in water service benchmarking studies since the 1990s. These techniques enable the comparison of the performance of a company or service in relation to those that define the efficient frontier, which represents the best practice observed (González-Gómez and García-Rubio, 2008). One example of using frontier methods as decision support tools is the study conducted by Alsharif et al. (2008) in Palestine. The study used frontier techniques to determine the efficiencies of municipal water systems and found that water losses were the primary source of inefficiency. These results can be used by Palestinian policymakers to prioritise infrastructure rebuilding efforts by starting with the most inefficient municipalities to minimise water losses.

According to Molinos-Senante et al. (2022b), Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) are the two most widely used methods for benchmarking water utilities, each having its advantages and disadvantages, and no definitive conclusion has been reached on which method is better for assessing water company efficiency. This lack of clarity has prompted doubts about the applicability of both techniques to benchmarking regulation in the water sector.

In the literature review conducted by Goh and See (2021), which analysed 142 articles spanning 20 years of benchmarking research in water utilities, it was found that DEA is more commonly used than SFA in the water sector. The review emphasised DEA's advantages, including its capability to combine multiple input-output combinations into a single efficiency measure in the production frontier and its flexibility, as it does not require a functional form for either production or cost functions, in contrast to SFA. The review also highlighted SFA's ability to account for the distinction between inefficiency and noise as an advantage. Standard DEA models present some limitations regarding the sensitivity to outlier data and the inability to allow for statistical inference. However, these issues have been addressed through the development of robust and conditional approaches. Marques et al. (2014); D'Inverno et al. (2021) and Mergoni et al. (2022) are examples of applications that use the robust and conditional developments in DEA. SFA methods have been applied to the water sector since 1993. Some developments of this approach are Lynk (1993); Bhattacharyya et al. (1995); Estache and Rossi (2002); Saal and Parker (2004) and Nyathikala et al. (2023).

DEA techniques can be utilised to create composite indicators (CIs), which involve the aggregation of multiple performance metrics to evaluate multidimensional performances. Vilanova et al. (2015) highlight the difficulties in defining the relative importance of those metrics for constructing

the overall indicator. Defining weights for the metrics requires creativity and experienced judgment to avoid subjectivity and frequently biased interpretations. However, using a DEA-based method offers the advantage of being data-driven, avoiding interacting with stakeholders to define the weights for the metrics. This approach, known as the “Benefit-of-the-Doubt” (BoD) strategy, which was popularised by Cherchye et al. (2007), has been implemented in various water sector management studies (Henriques et al., 2020; Mergoni et al., 2022; Sala-Garrido et al., 2021).

Another example of non-parametric method used in benchmarking is Free Disposal Hull (FDH). Originally developed as an alternative to DEA, FDH relaxes the convexity assumption of DEA. Although less commonly used than DEA or SFA, it has also been applied in the water industry. Studies on the applications of FDH in the water sector can be found in Hernández-Sancho et al. (2011) and Fuentes et al. (2015).

Water utility performance has often been evaluated using both parametric and non-parametric frontier techniques. The selection of a particular technique can depend on a range of factors, including data availability, adequate numbers of comparators, the incorporation of environmental variables, and the size of the companies being assessed. Each frontier technique operates on its own set of assumptions regarding the treatment of noise and inefficiency, resulting in potential disparities in efficiency estimates across various models (Molinos-Senante et al., 2022b).

Molinos-Senante et al. (2022b) conducted a study in Chile to compare the effectiveness of three frontier techniques in estimating efficiency scores for water utilities: DEA, SFA, and StoNED, which has been mainly used in the electricity sector. The results showed significant differences in efficiency scores across the three techniques due to their different underlying assumptions. However, the study highlights the overall inefficiency of the water industry, emphasising the importance of better management of daily operations and addressing issues such as leakage and unplanned interruptions. Furthermore, the study suggests that there is no single correct approach when measuring utilities’ performance, and policy makers, regulators, and researchers need to have a good understanding of industry structure, including costs, outputs, and environmental variables when conducting benchmarking analysis, as it can impact decision-making processes. Overall, this research reinforces the need for increased involvement and knowledge of industry structure in benchmarking analysis for effective decision-making.

Benchmarking practices have become increasingly important in the water sector for identifying areas of inefficiency and implementing strategies to improve utility performance. To this end, this thesis leverages frontier-based tools to conduct benchmarking exercises for the issues addressed in Chapters 4, 5, 6 and 7. A detailed explanation of the techniques utilised is presented in these upcoming chapters.

3.4 Conclusion

This chapter has outlined the utilisation of decision support tools that play a critical role in enhancing water utility management. The decision support tools developed in this thesis can help water utility managers overcome challenges in resource efficiency, service quality, and infrastructure

management, which are critical concerns in the water sector. Furthermore, these tools can support the water sector's efforts to cope with emerging trends. They can serve as building blocks for fostering digitalisation processes, enhancing sustainability, and minimising infrastructure risks.

Finally, the decision support tools presented in this thesis can foster organisational learning and continuous improvement, which are crucial for building internal capacity and achieving long-term success. By providing managers with actionable insights and performance benchmarks, these tools can facilitate the identification of best practices and support a culture of innovation and knowledge-sharing within water utilities. Overall, the decision support tools presented in this thesis represent valuable initiatives for enhancing the management and performance of water utilities, and for supporting the sector's efforts to address existing challenges.

A decision support model for cost efficiency assessment of wholesale water utilities under a regulatory context

This chapter proposes a comparative evaluation instrument designed to measure the efficiency of the water supply and wastewater treatment managing entities that operate in the wholesale market segment. The purpose of this instrument is to determine the efficient operating cost of each managing entity for the 2017-2021 period. To this end, the non-parametric Data Envelopment Analysis technique was used, adapted to a robust and conditional approach to mitigate the impact of outliers in estimating the production technology frontier and understand the influence of the surrounding context on the activity of the entities. The cloudy situation predicted for the water sector in the coming decades at an international level makes it possible to foresee several problems in terms of the scarcity of drinking water and access to basic sanitation conditions. For this reason, this sector assumes ideal characteristics for governance. In fact, through benchmarking, regulation can guide decision-making and control the position of operators in the market, promoting efficiency improvements. The proposed models were defined together with a European Union country regulatory entity for this sector. The results point to similar mean efficiency scores between both services in the 5 years in question. However, they revealed the existence of greater heterogeneity between entities managing the wastewater treatment service than the water supply service. Furthermore, the estimated potential savings for both ranged from 2% to 3%, approximately. The impact of the *Management model* and the *Typology of intervention area* on the efficiency levels proved to be statistically significant in the water supply service (only the latter) and the wastewater treatment service (both).

4.1 Introduction

Over the last few years, debates about some of the major challenges of the twenty-first century have intensified, from pandemics to wars, population growth to poverty, and climate change to energy crises. However, an issue at the centre of these discussions is often forgotten: the scarcity of water resources. According to the most recent report of the United Nations (UN; 2022), the world's water-related ecosystems are being degraded at an alarming rate, with more than 85% of the Earth's wetlands being lost in the past 300 years. Besides, over 700 million people live in countries with high and critical water stress levels. In the end, the UN predicts that, at the current rate, 1.6 billion people will lack safely managed drinking water by 2030 and a fourfold increase

in the pace of progress will be necessary to meet water supply and sanitation targets, despite the progressive convergence of its Member States towards them (Pereira and Marques, 2021, 2022a).

If we narrow our scope to the European context, we encounter a set of policies and strategies established by the European Commission to halt deterioration in European water bodies and improve their status. First, the Water Framework Directive (2000/60/EC) legislates the quality and quantity of groundwater and the quality of surface water. Most Central and Northern European countries have reported their River Basin Management Plans, while most Southern and Eastern European countries are still up to the public consultation stage. Second, the European Green Deal intends to guide the efficient use of resources in the sustainable circular economies of the future, resting on the Circular Economy Action Plan aimed at reducing the pressure on natural resources, with clean water as one of its primary goals.

However, the scenario for the water sector can be revamped by doing better with less. The Organisation for Economic Co-operation and Development (OECD; 2015) stated that this sector is highly aligned with the features of multi-level governance in that water connects all sectors, places, and people, and its management is both a global and local concern. The monopolistic nature of this sector (and associated market failures) turns policy-making into an intricate task. Indeed, the World Bank (1992) had already aligned a country's quality of governance - how power is utilised in managing a country's resources - with its level of development.

Furthermore, the OECD (2015) has also asserted that "water crises are often primarily governance crises". Despite lacking evidence supporting a one-size-fits-all solution to address global water challenges, a highly context-dependent governance framework, enhanced with bottom-up and inclusive decision-making in designing effective water policies, is key to overcoming bottlenecks and solving current and future water challenges. Essentially, the robustness of future public policies should rely on the dimensions of water governance put forward by the OECD (2015): effectiveness (concerning governance's contribution to set, implement, and meet targets), efficiency (concerning governance's contribution to maximise user sustainable water value for money), and trust and engagement (concerning governance's contribution to building public confidence and democratically involve all stakeholders).

The OECD's focus is more comprehensive than the user satisfaction-based effectiveness dimension (Vilanova et al., 2015). From an economic standpoint, it seeks to minimise resource consumption to produce the outcomes expected by the users. Fundamentally, it rests on four principles: data and information, financing, innovative governance, and regulatory frameworks. In particular, the latter is seen as a critical principle since regulatory authorities play a major role in supervising operators, monitoring all areas of water-related services, and deploying policies to balance the needs and expectations of the stakeholders (Akhmouch and Correia, 2016). Regulation is vital to control the operators' market position, quality of service, and prices - something that can be accomplished via benchmarking (Pereira and Marques, 2022b). Benchmarking actions are recognised as an essential tool to promote efficiency improvements in the water sector (Henriques et al., 2020). Regardless of the type of regulatory model, the literature has shown that benchmarking not only empowers the regulatory authority in guiding decision-making but also

introduces artificial competition in naturally monopolistic sectors and, consequently, incentivises improvements (Pinto et al., 2017b).

Nonetheless, Mehta et al. (2013) claim that the full potential of benchmarking tools in regulated sectors, such as urban water supply and sanitation, is yet to be achieved. Therefore, a systematic effort is needed to develop efficiency measurement tools to monitor water supply and wastewater treatment operators conducive to improving their price-quality relationship, quality of service, and system sustainability in the long term.

In this study, we conceive a comparative evaluation instrument to measure the efficiency of water supply and wastewater treatment service providers operating in the wholesale market segment in a European Union (EU) country in collaboration with its water and waste services regulatory authority. The result of this collaboration is to ascertain the efficient operating expenditure (OPEX) of each operator for the 2017-2021 period and support budget drafting for the next regulatory period, with clear impacts on the country's contributions towards the aforementioned European Commission's Water Framework Directive and European Green Deal policies in terms of water quality. In particular, we employ the ubiquitous Data Envelopment Analysis (DEA) non-parametric method, extended to a conditional and robust order- m setting to mitigate the impact of atypical operators and understand the influence of exogenous factors on the operational activity of the service providers. This way, our proposal is aligned with the state of the art of scientific literature on non-parametric efficiency measurement and uses a conditional and robust order- m approach as a benchmarking tool aimed at improving operational practices through peer learning. This work is also innovative since it comprehends a collaborative empirical application in the water supply and wastewater treatment wholesale market segment. The approach proposed in this study is innovative in terms of regulation in the European space, placing this country as a pioneer in terms of formative regulation for wholesale operations. It is tailored to promote continuous enhancement in the sector by providing regulatory authorities with tools that allow them to define improvement objectives based on comparisons with the best practices observed in other entities, taking into account the context in which they operate.

This chapter is structured as follows: Section 4.2 addresses the literature reviewed in the pursuit of the knowledge gap and identifies the aspects that differentiate this study from previous works; Section 4.3 details the methodology proposed for the efficiency analysis; Section 4.4 describes the case study built alongside the regulatory authority; Section 4.5 presents the results and discusses their regulatory and decision-making implications; Section 4.6 highlights the main achievements, limitations, and research prospects of the study.

4.2 Knowledge gap

There are numerous scientific publications regarding efficiency in the water sector, ranging from articles (see, e.g., Gidion et al., 2019; Fu and Jacobs, 2022) to book chapters (see, e.g., Davis, 2005) and reviews (see, e.g., Vilanova et al., 2015; Santos et al., 2019) to conference proceedings (see, e.g., Vieira et al., 2015; Dziedzic and Karney, 2014). These studies, and many others in the

literature, cover different perspectives in which measuring the efficiency of services provided in this sector is included. When it comes to studies on the efficiency of water supply and wastewater treatment services, the paradigm is quite different, especially if we consider the two segments of this market - wholesale and retail. First, focusing on the wholesale market segment was a request from the country's regulatory authority, which intended to begin an analytical endeavour upstream regarding the water supply and wastewater treatment value chain before delving into any regulatory market changes. Second, addressing potential barriers wholesale market operators create, in light of the sustainability issues raised in Section 4.1, is crucial for efficient governance, especially at the local government level (Caplan et al., 2022). Third, to the best of the authors' knowledge, there are only two studies on the wastewater treatment service (Carvalho and Marques, 2014; Henriques et al., 2020) that partially meet the wholesale market segment requirement - none of which have provided clear evidence for inefficiencies in the country's wholesale market. It should be noted that the number of studies in this area on the retail market segment is vastly broader, with much more detailed insights into the country, although there is no concrete focus on this niche of the literature in the analysis at the level of companies, municipalities, regions, or even other countries. Studies on wholesale water supply are non-existent as far as the authors are aware.

Indeed, both Carvalho and Marques (2014) and Henriques et al. (2020) conducted a benchmarking study of the wastewater treatment services operating in the wholesale market segment in Portugal. Nevertheless, while the former also included water supply operators and the retail market segment, the latter focused exclusively on wastewater treatment operators in the wholesale and retail market segments. First, Carvalho and Marques (2014) studied the existence of economies of vertical integration between the two market segments, economies of scope between water supply and wastewater treatment services, and economies of scale in the wholesale market segment using robust order- α DEA. The authors considered a total sample of 74 operators between 2002 and 2008 and evaluated them according to 3 different models (depending on the type of economies under assessment), always considering *Labour costs*, *Capital costs*, and *Other operational costs* as inputs and a mix of volumes as outputs (in particular, regarding wastewater treatment, they have considered the *Volume of collected wastewater* and the *Volume of treated wastewater*). Ultimately, the authors found evidence of economies of scale in wastewater treatment services operating exclusively in the wholesale market segment. Second, Henriques et al. (2020) proposed a benchmarking framework to support performance-based sunshine regulation in wastewater treatment services. Using DEA's 'Benefit-of-the-Doubt' (BoD) approach, formulated with a directional distance function and incorporating weight restrictions, the authors assessed the performance of a total of 212 wastewater treatment retailers and wholesalers in Portugal in 2018, considering the three dimensions (user interface suitability, service management sustainability, and environmental sustainability) and fourteen indicators proposed by the Portuguese regulatory authority for Water and Waste Services (ERSAR, 2021a) to evaluate the quality of service provided by wastewater treatment retailers and wholesalers. Their framework also included a second-stage contextual analysis. At last, the results of this study pointed to an exemplary level of performance

in 6 of the 12 operators of wastewater treatment services that operate in the wholesale market segment in the three considered dimensions but did not find evidence of exogenous variables capable of explaining the dispersion observed in the levels of inefficiency associated with the remaining operators. However, only 3 of the 200 operators of wastewater treatment services operating in the retail market segment achieved notable results along the three dimensions, even though, in this case, there is a positive impact on the quality of service by a larger scale, investment subsidies, and energy production as well as concessions and urbanisation.

The two studies described above address different aspects of the water supply and wastewater treatment sector in the wholesale market segment but share some similarities. Table 4.1 encapsulates their main features in terms of application context and model structure.

Table 4.1: Overview of the application context and model structure of studies on efficiency measurement on wholesale water supply and wastewater treatment services.

Reference	Application context			Model structure			Contextual variables
	Country	Sample	Year(s)	Methodology	Indicators	Output(s)	
					Inputs		
Carvalho and Marques (2014)	Portugal	74 wholesale and retail water supply and wastewater treatment services	2002-2008	Robust order- α DEA	Labour costs + Capital costs + Other operational costs	Volume of delivered water (retail) + Volume of delivered water (wholesale) + Volume of collected wastewater + Volume of treated wastewater	-
Henriques et al. (2020)	Portugal	12 wholesale wastewater treatment services + 200 retail wastewater treatment services	2018	Two stage DEA approach: directional BoD + hypothesis tests	Dummy variable (unitary input)	Physical accessibility of the service + Economic accessibility of the service + Occurrence of floods + Response to complaints and suggestions + Coverage of expenses + Subscription to the service + Rehabilitation of collectors + Occurrence of structural collapses in collectors + Adequacy of human resources + Energy efficiency of lifting installations + Physical accessibility to treatment + Control of emergency discharges + Compliance with the discharge license + Adequate forwarding of treatment sludge	Management model + Typology of the intervention area + Collected wastewater + Own energy production + Investment subsidies

If we extend the scope of our search to the retail market segment, the outcomes are quite different. There is a myriad of studies in several countries, namely: Ananda (2014) in Australia, Tourinho et al. (2022b,a) and Pereira and Marques (2022c) in Brazil, Maziotis et al. (2020) and Molinos-Senante et al. (2020) in Chile, Romano et al. (2018) in Italy, Satoh (2015) and Satoh (2019) in Japan, Ablanedo-Rosas et al. (2020) and Salazar-Adams (2021) in Mexico, Carvalho and Marques (2011) and Pinto et al. (2017c) in Portugal, Molinos-Senante and Maziotis (2018) and Williams et al. (2020) in England and Wales, Ferreira da Cruz et al. (2012) in Italy and Portugal, De Witte and Marques (2010a) in Australia, Belgium, England, the Netherlands, Portugal, and Wales, and Ferro and Romero (2011) in Latin America.

Bottom line, similarly to the previously reported publications on the wholesale market segment, these studies tend to use: labour, capital, and operational costs as inputs; volumes of delivered water and collected and treated wastewater as outputs; and geography and ownership as contextual variables (Tourinho et al., 2022b). The reader interested in water utility benchmarking is directed to the survey of Berg and Marques (2011) and the bibliometric analysis of Goh and See (2021) for further information on the subject.

Note that the vast majority of the studies mentioned above use some form of DEA (mainly the same approach as Lo Storto (2013)), with only Ferro and Romero (2011) (which also used DEA), Molinos-Senante and Maziotis (2018), Molinos-Senante et al. (2020), and Williams et al. (2020) using econometrics resting on the Stochastic Frontier Analysis (SFA) approach. Regarding robust conditional DEA, the order- m approach is more popular than its order- α counterpart, with applications of the former being found in the works of De Witte and Marques (2010a), Carvalho and Marques (2011), and Pinto et al. (2017c). However, while De Witte and Marques (2010a) conducted an international benchmarking study to design performance incentives for water utilities, both Carvalho and Marques (2011) and Pinto et al. (2017c) attempted to understand the influence of the operational environment on the Portuguese water utilities.

In the end, as far as we know, no studies apply robust conditional order- m DEA to measure the efficiency of water supply and wastewater treatment services operating in the wholesale market segment under a regulatory framework (in this EU country or abroad). Furthermore, there are no publications that do so as a result of a collaboration between academia and national regulatory authorities. Hence, the contributions of our proposal are reiterated as being twofold, both in terms of the scientific innovation of the used models and their empirical application to actual data underlying the regulation of water supply and wastewater treatment companies in the context of this EU nation.

4.3 Methodology

With the importance of benchmarking as a vital analysis for regulation activities in the water sector having already been established in Section 4.1, it is time to address its methodologies. Parametric and non-parametric frontier methods to measure efficiency have been employed in the sector, ranging from SFA to Data Envelopment Analysis (DEA), respectively, and their adaptations and extensions. However, Goh and See (2021) say that DEA has become the most popular.

As a non-parametric frontier method, DEA measures the relative efficiency of a homogeneous set of decision-making units (DMUs) producing multiple outputs from multiple inputs as the radial distance from each DMU to the estimated production frontier. It returns a group of efficient DMUs, i.e., benchmarks, and a group of inefficient DMUs. DEA optimises the weighting system that enables each DMU to yield its best efficiency score. It was designed by Charnes et al. (1978) based on the concepts proposed by Farrell (1957). Its main advantage concerns the nonnecessity of specifying the functional form of its frontier *a priori*, only making some assumptions regarding the production technology (e.g., convexity, returns-to-scale).

Resting on the literature review conducted in Section 4.2, it is consensual that an input-oriented VRS DEA model should be adopted in efficiency measurements in this sector. Thus, its envelopment formulation, which seeks the proportional input reduction needed for a certain DMU to reach the frontier assuming distinct scale sizes among the DMUs, for the DMU under assessment

(DMU_{*j*0}) is shown in Model (4.1):

$$\begin{aligned}
 Z_I = \min \quad & \theta_{j_0} - \varepsilon \left(\sum_{i=1}^m s_{ij_0}^- + \sum_{r=1}^s s_{rj_0}^+ \right) \\
 \text{subject to} \quad & \sum_{j=1}^n \lambda_j x_{ij} + s_{ij_0}^- = \theta_{j_0} x_{ij_0}, \quad i = 1, \dots, m \\
 & \sum_{j=1}^n \lambda_j y_{rj} - s_{rj_0}^+ = y_{rj_0}, \quad r = 1, \dots, s \\
 & \sum_{j=1}^n \lambda_j = 1 \\
 & \theta_{j_0} \text{ is free} \\
 & \lambda_j, s_{ij_0}^-, s_{rj_0}^+ \geq 0, \quad \begin{cases} j = 1, \dots, n \\ i = 1, \dots, m \\ r = 1, \dots, s \end{cases} \\
 & \varepsilon > 0,
 \end{aligned} \tag{4.1}$$

where: x_{ij} denotes the value of input i for DMU j ; y_{rj} denotes the value of output r for DMU j ; θ_{j_0} is a decision variable that denotes the radial efficiency score of DMU_{*j*0}; λ_j is a decision variable that denotes the intensity variables and assumes a positive value in case a specific DMU j is a peer of DMU_{*j*0}; $s_{ij_0}^-$ is a slack variable that denotes potential non-radial adjustments to the input levels of DMU_{*j*0}; $s_{rj_0}^+$ is a slack variable that denotes potential non-radial adjustments to the output levels of DMU_{*j*0}; and ε is a non-Archimedean infinitesimal.

After computing the optimal solution of Model (4.1), we obtain *fully efficient*, *weakly efficient*, and *fully inefficient* DMUs. DMU_{*j*0} is fully efficient when its efficiency score, θ_{j_0} , is equal to one and all slacks, $s_{ij_0}^-$ for $(i = 1, \dots, m)$ and $s_{rj_0}^+$ for $(r = 1, \dots, s)$, are equal to zero. A DMU is weakly efficient when its efficiency score, θ_{j_0} , is equal to one, but at least one slack, $s_{ij_0}^-$ for $(i = 1, \dots, m)$ or $s_{rj_0}^+$ for $(r = 1, \dots, s)$, is positive. Finally, a DMU is fully inefficient when its efficiency score, θ_{j_0} , is lower than one. Furthermore, it is possible to compute targets for an inefficient DMU_{*j*0} based on the optimal values of the decision variables of its peers (given by the symbol ‘*’) according to Expression (4.2) and Expression (4.3):

$$x_{ij_0}^T = \sum_{j=1}^n \lambda_j^* x_{ij} = \theta_{j_0}^* x_{ij_0} - s_{ij_0}^{*-}, \quad i = 1, \dots, m \tag{4.2}$$

$$y_{rj_0}^T = \sum_{j=1}^n \lambda_j^* y_{rj} = y_{rj_0} + s_{rj_0}^{*+}, \quad r = 1, \dots, s \tag{4.3}$$

Nevertheless, DEA’s deterministic nature poses a disadvantage in the face of outliers since any atypical observation belonging to the set of DMUs can shape the so-called *full frontier*. Consequently, their presence may shift that frontier and underestimate the scores of the remaining DMUs

(Fusco et al., 2020). Therefore, although detecting outliers to be removed from the sample can be useful, understanding the extent to which they are the best- or worst-performing DMUs may be of interest, especially in the case of small samples where information is crucial for decision-making (De Witte and Marques, 2010). The proposal of *partial/robust frontiers* has been put forward in the literature to address these issues, essentially in two ways: order- m (Cazals et al., 2002; Daraio and Simar, 2005, 2007b) and order- α (Aragon et al., 2005; Daouia and Simar, 2007) methods. In particular, order- m and order- α partial frontiers differ since the former concerns a “discrete” notion and the latter a “continuous” notion of partial frontiers given the fundamental distinction between m as a function of n and α as the level of an appropriate non-standard conditional quantile frontier (Daouia and Simar, 2007). If we look at Section 4.2, there is a quantitative preference in the literature for order- m methods instead of order- α ones supporting the use of the former over the latter.

In particular, unlike in the full frontier estimation via Model (4.1), where the model was solved iteratively per DMU, partial frontier estimation solves Model (4.1) B times per DMU following a Monte Carlo simulation, where B is a large number. Since we are dealing with an input-oriented analysis, m DMUs are randomly drawn with replacement among those producing an output level greater than or equal to the DMU _{j_0} in each B iteration. This subsampling procedure aims to mitigate the impact of outliers and compare the DMU _{j_0} with less extreme peers¹. In the end, the mean of the efficiency scores computed per b -th iteration, with $b = 1, \dots, B$, $\theta_{j_0}^{b,m}$ is equal to the robust order- m efficiency score $\hat{\theta}_{j_0}^m$:

$$\hat{\theta}_{j_0}^m = \frac{\sum_{b=1}^B \theta_{j_0}^{b,m}}{B} \quad (4.4)$$

On the one hand, m can be seen as the number of DMUs competing with the DMU _{j_0} to produce greater or equal output levels. On the other hand, it can be seen as a threshold value for the robustness analysis. The choice of m is not elementary since the literature mentions that its value should not be too high or too low because of the possibility of not enveloping all DMUs (Cazals et al., 2002; Rogge and De Jaeger, 2013). Typically, m should be lower than the number of sampled DMUs to decrease the probability of super-efficient DMUs. Henriques et al. (2022) suggest conducting a sensitivity analysis for different m values to support the robustness of the analysis.

When identifying benchmarks and targets in a robust order- m DEA context, there are some possibilities to compute them, following Henriques et al. (2022). First, the number of times a DMU is deemed as a benchmark per partial frontier indicates its benchmarking status. Second, the intensity variables and the targets can be computed as the mean of all B iterations. Since a partial frontier produces a tighter envelope around the sampled data, the generated robust efficiency scores will always be higher than those computed from a full frontier estimation. Thus, the robust target values will be lower and more realistically achievable.

¹Nonetheless, it may lead to the absence of DMU _{j_0} among the subsampled m DMUs. Hence, it may be located above the partial frontier and be identified as a *super-efficient* DMU if its efficiency score is greater than one.

Moreover, understanding the influence of the operational context is of utmost importance in these types of analyses. Ascertaining the role of specific factors surrounding the sampled DMUs is usually recognised by the literature as a relevant aspect, typically addressed via a *one-stage approach* (where contextual variables are classified *a priori* as either inputs or outputs and included in the model or used to guide the sampling procedure) or a *two-stage approach* (where efficiency scores are computed in a first stage and parametrically regressed on non-discretionary variables in a second stage) (Daraio and Simar, 2007b). However, depending on the type of contextual variable, a mixed approach can be used, for instance, considering continuous/*modelling* contextual variables in the first stage and categorical/*descriptive* contextual variables in the second stage. Still, according to those authors, there are two issues concerning the bias of first-stage efficiency scores and the need for specifying the parametric regression model *a priori*. For this reason, Daraio and Simar (2005) proposed conditional non-parametric frontier models, whose insights were integrated into the robust conditional DEA employed here, also in line with Daraio and Simar (2007b) and De Witte and Kortelainen (2013).

Compared to the robust order- m DEA described above, the robust conditional order- m DEA demands an adjustment to estimate the unconditional frontier. This way, there is a higher probability of DMUs that operate in a similar context being drawn together and a lower probability of DMUs that operate in a different context being drawn together. Accordingly, the mean of the conditional efficiency scores computed per b -th iteration, with $b = 1, \dots, B$, $\theta_{j_0}^{b,m,z}$ is equal to the robust conditional order- m efficiency score $\hat{\theta}_{j_0}^{m,z}$:

$$\hat{\theta}_{j_0}^{m,z} = \frac{\sum_{b=1}^B \theta_{j_0}^{b,m,z}}{B} \quad (4.5)$$

Note that R version 4.2.1 was the software used to implement the models above and compute the results. In particular, the ROBUST_DEA and CONDITIONAL_DEA of the RCDEA package were employed with slight code modifications to enable the benchmark computation.

4.4 Case study

This section covers the application context addressed in this study (Subsection 4.4.1) and the modelling structure used to address it (Subsection 4.4.2).

4.4.1 Application context

The challenges faced by the water sector and the goals set to tackle them are two key facets of regulation (Henriques et al., 2020). This case considers an unidentified EU country in which the regulatory authority developed an integrated approach comprising two perspectives: structural regulation and behavioural regulation. Although the former concerns organisational aspects and the latter concerns each utility, both standpoints should interact and evolve (Baptista, 2014b).

Essentially, the sunshine regulatory model adopted by the regulatory authority is portrayed as collaborative rather than restrictive. It uses a set of transparent key performance indicators to evaluate the service quality of operators according to three dimensions - user interface suitability, service management sustainability, and environmental sustainability - and, ultimately, enable regulation by benchmarking to impact the operators' performances and promote accountability, thus assuming a developmental role in the sector instead of a monitoring and control part.

The market structure of the water sector in that nation is divided into wholesale and retail market segments, with the latter being less developed than the former from service quality, resource management, and sustainability standpoints (ERSAR, 2021a). As justified above, this study focuses on wholesale water supply and wastewater treatment services, which currently comprehend 17 and 12 operators covering 72% and 96% of the country's population, respectively. Note that three entities operate simultaneously as both wholesalers and retailers (ERSAR, 2021a), although their data sets are completely separate, including cost information.

Bottom line, the water supply or wastewater treatment service providers analysed in this chapter are studied in the 2017-2021 period as pooled five-year samples but must remain anonymous due to confidentiality issues. In this work, only 10 of the 17 water supply service providers operating in the wholesale market segment were considered since the remaining 7 provide the service in very restricted areas. Thus, 50 observations populated all water supply (WS) models, resulting from 10 observations per year, i.e., five observations per operator. As for the wastewater treatment service, six instances were removed from the sample. This deletion was due to reasons related to significant changes in the production technology of these service providers in the years considered according to the EU country's regulatory authority. Hence, 54 observations (due to the removal of 6 observations from the initial 60 observations, which resulted from 12 observations per year, i.e., five observations per operator) populated all wastewater treatment (WT) models. Additionally, there are six common operators between the ten water supply and 12 wastewater treatment sets, i.e., 16 distinct operators in total. In the end, 7 out of the ten sampled wholesale water supply operators and 10 out of the 12 sampled wholesale wastewater treatment operators are managed under a municipal or multi-municipal concession agreement, while 3 of 10 and 1 of 12 abide by a delegated State or municipal management solution, and municipal or inter-municipal services or associations directly manage 1 of 12.

4.4.2 Modelling structure

The assessment carried out in this chapter required the collaborative construction with the regulatory authority of the production activities of the WS and WT service providers operating in the wholesale market segment. This way, two efficiency measurement models - a robust unconditional (RU) one and a robust conditional (RC) one - were defined per type of service in the wholesale market segment, depending on whether or not the modelling contextual variable was included in the RC model: WS-RC MODEL and WT-RC MODEL if the modelling contextual variable was considered in the RC model; WS-RU MODEL and WT-RU MODEL if the modelling contextual variable is not included in the RU model (see Table 4.2).

Table 4.2: Modelling structure of WS MODELS and WT MODELS.

Model	Indicators		Contextual variables	
	Input	Outputs	Modelling	Descriptive
WS-RC	Total OPEX (x_1^{WS})	Volume of water entering the system (y_1^{WS}) + Elevated volume of water (y_2^{WS}) + Number of households with effective water supply service (y_3^{WS}) + Total length of pipelines (y_4^{WS})	Raw water quality (z_1^{WS})	Management model (z_2^{WS}) + Typology of the intervention area (z_3^{WS})
WS-RU	Total OPEX (x_1^{WS})	Volume of water entering the system (y_1^{WS}) + Elevated volume of water (y_2^{WS}) + Number of households with effective water supply service (y_3^{WS}) + Total length of pipelines (y_4^{WS})	-	Management model (z_2^{WS}) + Typology of the intervention area (z_3^{WS})
WT-RC	Total OPEX (x_1^{WT})	Volume of wastewater treated in treatment plants (y_1^{WT}) + Elevated volume of wastewater (y_2^{WT}) + Number of households with effective wastewater treatment service (y_3^{WT}) + Total length of collectors (y_4^{WT})	Effluent quality (z_1^{WT})	Management model (z_2^{WT}) + Typology of the intervention area (z_3^{WT})
WT-RU	Total OPEX (x_1^{WT})	Volume of wastewater treated in treatment plants (y_1^{WT}) + Elevated volume of wastewater (y_2^{WT}) + Number of households with effective wastewater treatment service (y_3^{WT}) + Total length of collectors (y_4^{WT})	-	Management model (z_2^{WT}) + Typology of the intervention area (z_3^{WT})

Essentially, the rationale behind the production process shown in Table 4.2 corresponds to the context of the physical configuration of the wholesale water supply and wastewater treatment systems according to the regulatory authority. In terms of the total operating costs, all the water that enters the system through an elevating process and serves retailers through pipelines is considered. Regarding the total operating costs, all wastewater collected from retailers through collectors and raised to be subjected to treatment is considered. It should be noted that an elevating process is for the (waste)water to circulate under pressure and enable it to overcome terrain barriers.

From another angle, following the recommendation of Henriques et al. (2022), we have chosen values of m equal to the number of DMUs in the samples ($m = 50$ for WS MODELS and $m = 54$ for WT MODELS) due to the small sample size of our study. This choice is supported by Daraio and Simar (2007a) since the authors state that even if m is independent of the sample size, its values can be fixed by taking into consideration the possible number of competitors of a given firm, which, in a market with a small number of utilities - as is the wholesale water supply and wastewater treatment one in this EU country -, it is sensible to consider all of them as potential competitors. $B = 1000$ was also chosen as the appropriate number of iterations for each model since it requires less computational effort. Running a sensitivity analysis on B did not generate changes, especially for larger values.

4.4.2.1 Input

It is important to note that the operating costs chosen as the input of each model include the *Cost of goods sold and materials consumed*, the *Cost of external supply and services*, the *Cost of labour*, and *Other operating costs*. The regulatory authority considered these four types of cost to be fundamental for the operational cost structure of wholesale service providers and, consequently, for the definition of OPEX. In other words, OPEX resulted from the sum of the *Cost of goods sold and materials consumed*, the *Cost of external supply and services*, the *Cost of labour*, and *Other operating costs*. Bear in mind that it does not include structure costs.

4.4.2.2 Outputs

After extensive discussions with the regulatory authority about the duality of operation in the wholesale and retail market segments, it was concluded that the system characteristics of the two types of services considered here would be a basis for choosing the outputs (see Subsection 4.4.1). Therefore, it is essential to consider as outputs the *Volume of water entering the system*, the *Elevated volume of water*, the *Number of households with effective water supply service*, and the *Total length of pipelines* in the case of the water supply service and the *Volume of wastewater treated in treatment plants*, the *Elevated volume of wastewater*, the *Number of households with effective wastewater treatment service*, and the *Total length of collectors* in the case of the wastewater treatment service.

4.4.2.3 Contextual variables

The selected contextual variables reconcile the evidence found in the literature and the regulatory authority's preferences. On the one hand, the chosen descriptive contextual variables were based on the ones most commonly used in the literature, namely the *Management model* (concession, delegation, or direct management) and the *Typology of the intervention area* (predominantly rural area, moderately urban area, and predominantly urban area). In particular, regarding the former (Vilarinho et al., 2023c): in a concession model, the State establishes a long-term public-private partnership with a third party to operate the system; in a delegation model, the State owns and controls the operation of the system, but delegates its management to an operator via a management contract; in a direct management model, the State owns and operates the system. Regarding the latter, its three typologies are derived from the degree of urbanisation of a territory established by the country's National Institute for Statistics. On the other hand, the modelling contextual variable boiled down to the quality of the product, depending on the model: *Raw water quality* in WS MODELS and *Effluent quality* in WT MODELS. Note that the latter was developed internally by the regulatory authority specifically for this analysis.

Briefly, the modelling contextual variable enters each robust conditional DEA model (WS-RC MODEL and WT-RC MODEL) in the optimisation process associated with the efficiency measurement, whereas the remaining contextual variables are considered only in a phase after obtaining the efficiency scores of the four models due to their descriptive nature. Thus, the descriptive contextual variables are not taken into account for the estimation of the production frontiers.

4.4.2.4 Overview

Finally, the descriptive statistics of all the variables used in the WS MODELS (Table A.1) and the WT MODELS (Table A.2) in the period 2017-2021 are reported in Appendix A.1.1. Regarding the descriptive contextual variables, given their use *a posteriori* and their invariable nature over time, their descriptive statistics are presented in the same appendix, but in Table A.3.

That being said, bivariate Pearson correlation tests were performed between all potential variables considered in the discussions with the regulatory authority to validate the choice of inputs and outputs. These varied between total OPEX, OPEX without structure costs, and structure costs for inputs and volumes, installed capacities, and socio-demographic indicators for outputs and modelling contextual variables of WS MODELS and WT MODELS in 136 correlations between 16 variables. These findings attest to the legitimacy of the modelling choices given the compliance with the isotonicity property of DEA, i.e., the requirement that the relationship between inputs and outputs is not erratic. For reasons of space, only the results concerning the selected variables are presented (see Table 4.3 and Table 4.4).

Several positive and statistically significant correlations between the chosen input and the selected outputs validate the regulatory authority's choices. Additionally, due to the positive and statistically significant correlation between almost all pairs of outputs of each model, adding or replacing some of them with other indicators could have been a reality. Infrastructure-related

Table 4.3: Bivariate Pearson correlation among the variables selected for WS MODELS.

	$x_1^{WS\ a}$	$y_1^{WS\ b}$	$y_2^{WS\ c}$	$y_3^{WS\ d}$	$z_1^{WS\ e}$	$y_4^{WS\ f}$
$x_1^{WS\ a}$	1	0.886**	0.796**	0.920**	-0.591**	0.652**
$y_1^{WS\ b}$	-	1	0.924**	0.887**	-0.405**	0.310*
$y_2^{WS\ c}$	-	-	1	0.887**	-0.284*	0.161
$y_3^{WS\ d}$	-	-	-	1	-0.406**	0.433**
$z_1^{WS\ e}$	-	-	-	-	1	-0.549**
$y_4^{WS\ f}$	-	-	-	-	-	1

^a Total OPEX^b Volume of water entering the system^c Elevated volume of water^d Number of households with effective water supply service^e Raw water quality^f Total length of pipelines

** Significance level of 1%

* Significance level of 5%

Table 4.4: Bivariate Pearson correlation among the variables selected for WT MODELS.

	$x_1^{WT\ a}$	$y_1^{WT\ b}$	$y_2^{WT\ c}$	$y_3^{WT\ d}$	$z_1^{WT\ e}$	$y_4^{WT\ f}$
$x_1^{WT\ a}$	1	0.890**	0.646**	0.934**	0.179	0.808**
$y_1^{WT\ b}$	-	1	0.697**	0.969**	0.169	0.559**
$y_2^{WT\ c}$	-	-	1	0.741**	0.300*	0.550**
$y_3^{WT\ d}$	-	-	-	1	0.289*	0.695**
$z_1^{WT\ e}$	-	-	-	-	1	0.375**
$y_4^{WT\ f}$	-	-	-	-	-	1

^a Total OPEX^b Volume of wastewater treated in treatment plants^c Elevated volume of wastewater^d Number of households with effective wastewater treatment service^e Effluent quality^f Total length of collectors

** Significance level of 1%

* Significance level of 5%

indicators, namely, the *Number of installations*, were a possibility. Nevertheless, the decision was made by the regulatory authority not to include them due to less strong correlations with other indicators.

It should be noted the considerable effort by the regulatory authority to provide clean panel data for all service providers to enable a careful analysis and an in-depth specification of the variables to be included in the models.

4.5 Results and discussion

This section contains the results and their discussion regarding the measurement of efficiency, computation of peers, and calculation of the ideal targets of the water supply and wastewater treatment service providers operating in the wholesale market segment. Subsection 4.5.1, Subsection 4.5.2, and Subsection 4.5.3 encompass these findings.

4.5.1 Water supply

On average, between 2017 and 2021, if we consider only the entities for which there is evidence of inefficiency ($\theta_{j_0} < 1$), water supply service providers obtained a mean score of approximately 0.9528 and 0.9541 according to the WS-RU MODEL and the WS-RC MODEL, respectively. In particular, between 2017 and 2021, 40% of the service providers were considered inefficient, according to both models. All scores ranged from 0.8731 to 2.5116 and 0.8731 to 1.0000 in the five considered years, respectively. The influence of outliers is evident when *Raw water quality* is not considered a modelling context variable since the service providers are being compared with very similar peers in the WS-RC MODEL.

Figure 4.1 details the evolution of the mean efficiency scores per year and methodology, considering all observations each year. The evolution trend of the efficiency scores points to a decrease during the period considered according to both models, with the lowest average value being reached in 2020. Table A.4 in Appendix A.1.2 provides further details on these results.

Ideally, service providers located below the efficient frontier should guide their improvement process by considering the performance levels observed in one or more peers. It should be noted that the fact that the study sample was relatively small, combined with using a modelling context variable in the WS-RC MODEL, resulted in an internal benchmarking exercise. External benchmarking occurred in four cases for the WS-RU MODEL out of 18 inefficient DMUs. Consequently, per year, each inefficient service provider generally has an ideal peer corresponding to itself in another year. 2017 was the year that emerged more frequently in the generated peers.

Thus, it is relevant to study the role of the descriptive contextual variables on the computed efficiency scores. Consequently, non-parametric hypothesis tests appear as the indicated approach; hence, the Kruskal-Wallis H test was applied to the groups of sampled utilities to assess the existence of statistically significant differences between their efficiency scores. In particular, the null hypothesis states that k samples are derived from the same population: if the hypothesis is true, the distribution of the obtained efficiency scores is not statistically significant; otherwise, rejection

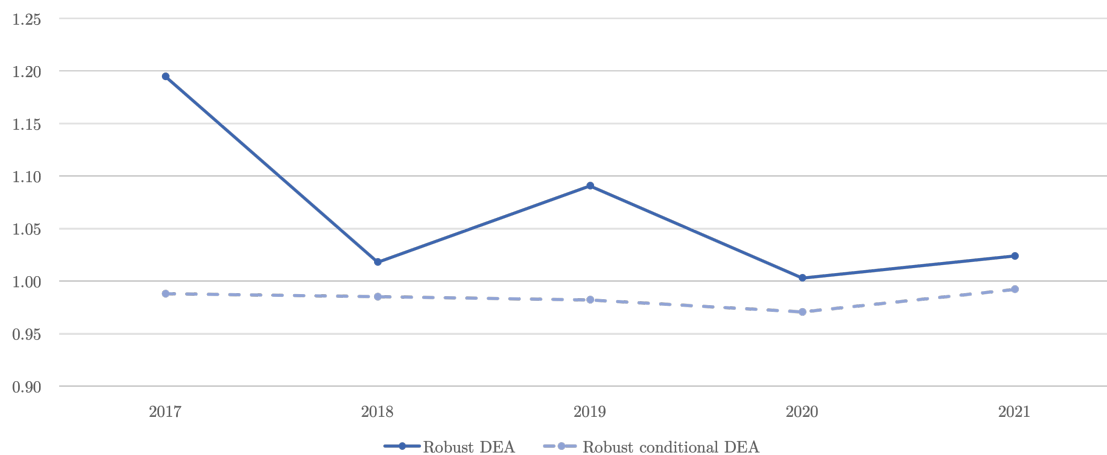


Figure 4.1: Annual evolution of average efficiency scores for the wholesale water supply service per model.

of the null hypothesis occurs at a significance level of 95% if the p -value is equal to or less than 0.05.

The results presented in Table 4.5 point to the retention of the null hypothesis in all cases except for the *Typology of the intervention area* in the WS-RU MODEL, which indicates that this contextual variable has a statistically significant influence on the efficiency scores of the wholesale water supply service providers when *Raw water quality* is not considered.

Table 4.5: p -values of the Kruskal-Wallis H tests for the descriptive contextual variables of the water supply service.

MODEL	Management model	Typology of the intervention area
WS-RU	0.915	0.001*
WS-RC	0.371	0.415

* Significance level of 5%

Additionally, accounting for the statistically significant differences in the distribution of efficiencies in the WS-RU MODEL in terms of the *Typology of the intervention area*, it is necessary to perform paired Mann-Whitney U tests to understand the source of statistically significant differences among intervention areas. Table 4.6 presents the results of these tests already adjusted for the Bonferroni correction. Indeed, the comparisons revealed statistically significant differences for ‘Predominantly rural area’ vs. ‘Moderately urban area’ and ‘Predominantly rural area’ vs. ‘Predominantly urban area’. The same did not occur for ‘Moderately urban area’ vs. ‘Predominantly urban area’. In other words, predominantly rural areas are distinct from moderately and predominantly urban areas, evident in their higher mean efficiency scores (1.2379 vs. 1.0012 and 1.2379 vs. 0.9702, respectively). We could not detect statistically significant differences in the WS-RC MODEL due to the small sample size, and the robust conditional model compares service providers operating in a similar context, which further reduces the comparison potential.

Table 4.6: p -values of the Mann-Whitney U tests for the *Typology of the intervention area* in the WS-RU MODEL.

	<i>Typology of the intervention area</i>		
	Predominantly rural area	Moderately urban area	Predominantly urban area
<i>Typology of the intervention area</i>	Predominantly rural area	-	0.012*
	Moderately urban area	-	0.473
	Predominantly urban area	-	-

* Significance level of 5%

At last, to test the relevance of operating simultaneously in the wholesale and retail market segments on the computed efficiency scores, another Mann-Whitney U test was applied to the groups of sampled utilities. However, the null hypothesis was retained in both the WS-RU MODEL and the WS-RC MODEL, implying that operating in the two market segments or only in the wholesale one does not significantly influence the efficiency scores.

4.5.2 Wastewater treatment

On average, between 2017 and 2021, if we consider only the entities for which there is evidence of inefficiency ($\theta_{j_0} < 1$), wastewater treatment service providers obtained a mean score of 0.9378 and 0.9507 according to the WT-RU MODEL and the WT-RC MODEL, respectively - values somewhat similar to those generated by the WS-RU MODEL and the WS-RC MODEL. In particular, between 2017 and 2021, 25% of the service providers were considered inefficient, according to both models. All scores ranged from 0.8266 to 3.0230 and 0.8380 to 1.0000 in the five considered years, respectively. In this case, the influence of outliers is evident when *Effluent quality* is not considered a modelling context variable since the service providers are being compared with very similar peers in the WT-RC MODEL.

Figure 4.2 details the evolution of the mean efficiency scores per year and methodology, considering all observations each year. The evolution trend of the efficiency scores points to an increase during the period considered according to the WT-RU MODEL and a slight decrease according to the WT-RC MODEL. Table A.5 in Appendix A.1.2 provides further details on these results.

As for the water supply service, service providers located below the efficient frontier should guide their improvement process by considering the performance levels observed in one or more peers. Once again, it should be noted that the fact that the study sample was relatively small, combined with using a modelling context variable in the WT-RC MODEL, resulted in an internal benchmarking exercise. External benchmarking occurred in six cases for the WT-RU MODEL out of 16 inefficient DMUs. Consequently, per year, each inefficient service provider generally has an ideal peer corresponding to itself in another year. 2018 was the year that emerged more frequently in the generated peers.

Thus, it is relevant to study the role of the descriptive contextual variables on the computed efficiency scores. Similarly to the previous service, non-parametric hypothesis tests in the same conditions appear as the indicated approach. This way, the results presented in Table 4.7 point

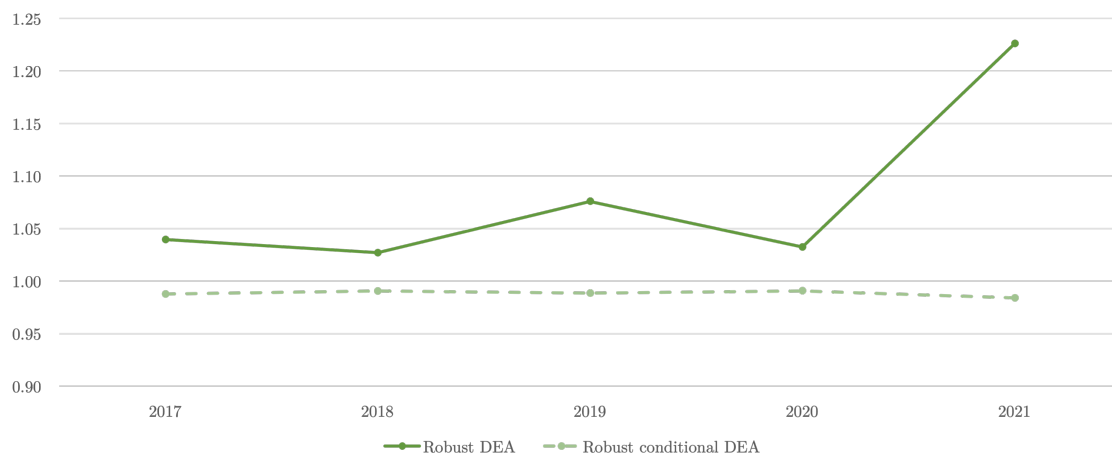


Figure 4.2: Annual evolution of average efficiency scores for the wholesale wastewater treatment service per model.

to the rejection of the null hypothesis in all cases except for the *Management model* in the WT-RC MODEL, which indicates that the remaining contextual variables statistically influence the efficiency scores of the wholesale wastewater treatment service providers.

Table 4.7: p -values of the Kruskal-Wallis H tests for the descriptive contextual variables of the wastewater treatment service.

MODEL	<i>Management model</i>	<i>Typology of the intervention area</i>
WT-RU	0.001*	< 0.001*
WT-RC	0.314	0.007*

* Significance level of 5%

Additionally, accounting for the statistically significant differences in the distribution of efficiencies in the WT-RU MODEL in terms of the *Management model* and the *Typology of the intervention area* and the WT-RC MODEL in terms of the *Typology of the intervention area*, it is necessary to perform paired Mann-Whitney U tests to understand the source of statistically significant differences among management models and intervention areas. Table 4.8, Table 4.9, and Table 4.10 present the results of these tests already adjusted for the Bonferroni correction. First, the comparisons of the results of the *Management Model* of the WT-RU MODEL revealed statistically significant differences for ‘Concession’ vs. ‘Delegation’ and ‘Concession’ vs. ‘Direct management’. In other words, concession models are distinct from the delegation and direct management models, which is evident in their lower mean efficiency scores (1.0509 vs. 1.0520 and 1.0509 vs. 1.6406, respectively). This finding implies that when the State only participates in an operator’s capital instead of owning or operating it, the service seems less efficient. However, note that only one operator is managed under a delegation model and another one under a direct management model, which means that these results should be interpreted cautiously. We could not detect statistically significant differences in the WT-RC MODEL due to the small sample size and the fact that the robust conditional model compares service providers operating in a similar

context, which further reduces the comparison potential. Second, comparing the results of the *Typology of the intervention area* of the WT-RU MODEL revealed statistically significant differences for ‘Predominantly rural area’ vs. ‘Moderately urban area’ and ‘Predominantly rural area’ vs. ‘Predominantly urban area’. In other words, predominantly rural areas are, once again, distinct from moderately and predominantly urban areas, which is evident in their higher mean efficiency scores (1.2464 vs. 1.0603 and 1.2464 vs. 0.9755, respectively). Third, comparing the *Typology of the intervention area* results from the WT-RC MODEL revealed statistically significant differences for ‘Moderately urban area’ vs. ‘Predominantly urban area’. In other words, moderately urban areas are distinct from predominantly urban areas, given their higher mean efficiency scores (0.9984 vs. 0.9664).

Table 4.8: *p*-values of the Mann-Whitney *U* tests for the *Management model* in the WT-RU MODEL.

		<i>Management model</i>		
		Concession	Delegation	Direct management
<i>Management model</i>	Concession	-	0.032*	0.013*
	Delegation	-	-	1.000
	Direct management	-	-	-

* Significance level of 5%

Table 4.9: *p*-values of the Mann-Whitney *U* tests for the *Typology of the intervention area* in the WT-RU MODEL.

		<i>Typology of the intervention area</i>		
		Predominantly rural area	Moderately urban area	Predominantly urban area
<i>Typology of the intervention area</i>	Predominantly rural area	-	< 0.001*	0.001*
	Moderately urban area	-	-	1.000
	Predominantly urban area	-	-	-

* Significance level of 5%

Table 4.10: *p*-values of the Mann-Whitney *U* tests for the *Typology of the intervention area* in the WT-RC MODEL.

		<i>Typology of the intervention area</i>		
		Predominantly rural area	Moderately urban area	Predominantly urban area
<i>Typology of the intervention area</i>	Predominantly rural area	-	1.000	0.072
	Moderately urban area	-	-	0.007*
	Predominantly urban area	-	-	-

* Significance level of 5%

Finally, an additional Mann-Whitney *U* test was applied to the groups of sampled utilities to test the relevance of operating simultaneously in the wholesale and retail market segments on the computed efficiency scores. Once again, the null hypothesis was retained in both the WT-RU MODEL and the WT-RC MODEL, implying that operating in the two market segments or only in the wholesale one does not significantly influence the efficiency scores.

4.5.3 Estimated savings

Finally, the total OPEX target an inefficient service provider needs to achieve based on the comparison with the values of its peers in order to become efficient must be known. Indeed, for regulatory purposes, it is recommended that such targets should be estimated via robust conditional models to ensure a more homogeneous comparison since they correspond to a more complete and conservative approach in terms of what is considered to be the effective potential for improvement in the sector. Nonetheless, we present the results of both models for comparison purposes.

Therefore, using Expression (4.2), it is estimated that the sum of the ideal total OPEX for the considered period varies between 13,431,583.54 € and 13,699,473.68 € for the water supply service and between 19,188,431.38 € and 26,590,580.70 € for the wastewater treatment service. This would allow average annual savings between 2.13% and 2.18% for the former and 2.36% and 3.22% for the latter. Figure 4.3 and Figure 4.4 show the total potential annual savings for each service based on these targets. It should be noted that the ideal total OPEX values are computed based on the outputs produced by each service provider, which justifies the reported annual variations.

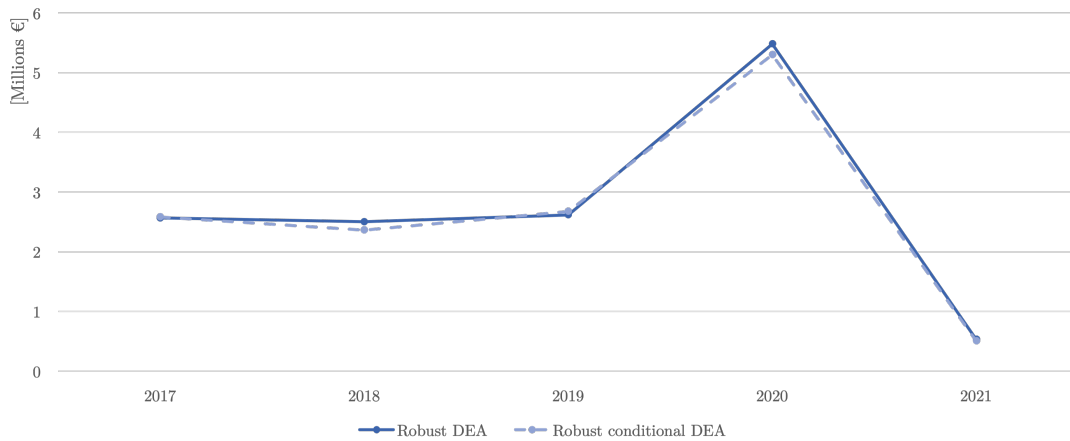


Figure 4.3: Potential annual savings for the water supply service.

It should be noted that entities for which there is evidence of super-efficiency ($\theta_{j_0} > 1$), in line with Mergoni et al. (2022), are DMUs that are doing better than the average m DMUs they are compared with (De Witte and Schiltz, 2018), which means that they do not need to reduce OPEX and their optimal OPEX value is the same as their original one.

4.6 Conclusion

This work addressed the problem of measuring the efficiency of the water supply and wastewater treatment service providers operating in the wholesale market segment in an EU country between 2017 and 2021. For this purpose, two methodologies with consolidated theoretical bases were employed in collaboration with the country's regulatory authority, being able to benchmark these

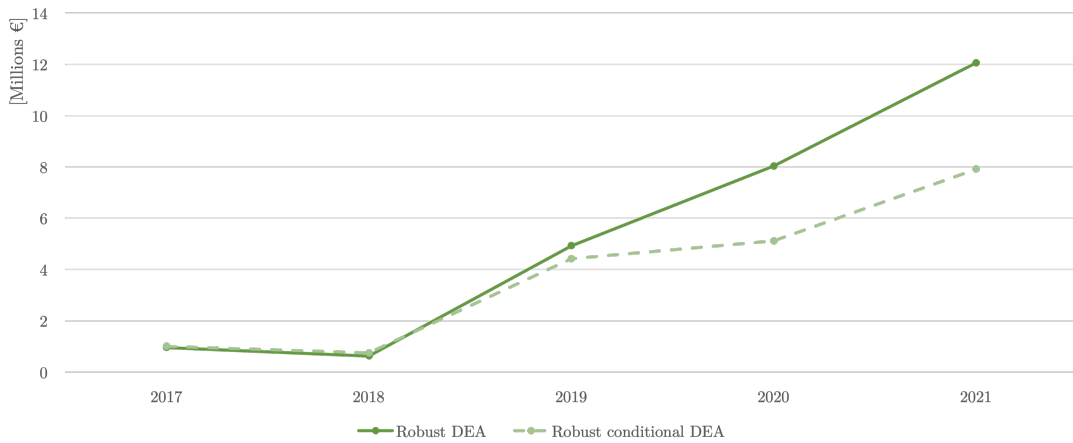


Figure 4.4: Potential annual savings for the wastewater treatment service.

services, avoid the impact of *outliers*, and allow the understanding of contextual factors. Fundamentally, the country's regulatory authority was involved in every process step, from selecting the sample and choosing suitable inputs, outputs, and contextual variables to critically analysing the results.

Nonetheless, robust conditional models should be considered the more accurate and conservative instruments for regulatory purposes. The regulatory authority saw such models as invaluable regulation tools with plenty of potential for future regulatory frameworks, such as monitoring service quality and setting efficient water tariffs. Moreover, by adopting a sunshine regulation strategy, the regulator can leverage the findings of this study to simulate market competition and encourage the operators to meet benchmark efficiency levels. Hence, they can ascertain the best practices of their peers and attain more favourable OPEX levels.

The results point to similar efficiency scores between the wastewater treatment service and the water supply service in the five years in question, although being slightly higher in the former (1.08 and 0.99 vs. 0.99 and 0.98 for the robust approach and the conditional approach to each service). In addition, it is estimated that, for the level of production of the service providers in each service, it is possible to save 2.13% (robust approach) and 2.18% (conditional approach) and 2.36% (robust approach) and 3.22% (conditional approach) of their respective average yearly total OPEX, which corresponds to 2,739,894.74 € (robust approach) and 2,686,316.71 € (conditional approach) for the former and 5,318,116.14 € (robust approach) and 3,837,686.28 € (conditional approach) for the latter. It should be noted that the *Management model* and the *Typology of the intervention area* showed statistically significant differences in terms of their role in influencing the efficiency scores obtained.

As main limitations, we point out three aspects. First, the availability and quality of some data motivated the use of *Raw water quality* and *Effluent quality* in their present form (developed internally by the regulatory authority specifically for this analysis) as *proxies*. Second, the positive and statistically significant correlation between almost all pairs of outputs of each model could motivate the addition or replacement of some of them by other indicators. Third, the con-

ditional nature of one of the methodologies transforms an external benchmarking exercise (given the comparison of a service provider with others) into an internal benchmarking exercise (since each service provider, when inefficient, becomes its own peer); for this reason, and allied to the reduced sample size, it was not possible to study the impact of the modelling contextual variables on the results by comparing the use of conditional and non-conditional models. The continued improvement of these shortcomings will lead to results even more suited to the fine-tuning of this collaborative regulatory framework, which will result in more transparent regulation and more efficient governance of the water sector. Alternative DEA methodologies should also be considered, e.g., window DEA to deal with the multi-period nature of the samples, meta-frontier DEA to account for the categorical contextual variables, and output-side weight restrictions based on the regulatory authority's preferences. Multi-criteria decision analysis-based approaches should also be considered to incorporate multiple stakeholders' value judgements further and ease the consensus-reaching process.

Assessing the quality of service of water utilities from a customer perspective to support sunshine regulation

This work delves into the crucial role of service quality in the water supply and sanitation sector. Despite extensive research and implementation of quality management practices in this sector, a universally accepted definition of quality is still lacking, resulting in various service quality assessment procedures that are difficult to compare. To address this issue, the World Bank launched the ‘Utility of the Future’ (UoF) program, aiming to guide water service providers in their efforts to become future-focused utilities that offer reliable, safe, inclusive, transparent, and responsive services through best-fit practices. Building upon the framework provided by the UoF program, this study proposes the Water Utility Service Quality Index (WUSQI) - a composite indicator that reflects the quality of service provided by water supply and sanitation utilities from a customer perspective. Based on Data Envelopment Analysis, the Benefit-of-the-Doubt approach is employed to assign weights for aggregating the indicators representing the diverse performance dimensions. The study operationalises the WUSQI to assess the quality of Portuguese wholesale water and wastewater companies using data collected by the national regulator of water and waste services. A Multiple Criteria Decision Analysis technique, the Deck of Cards method, is used to specify an indicator of transparency from the information made available by the regulated utilities. The results show the effectiveness of this tool for evaluating and measuring service quality at the company level. Additionally, the findings highlight areas for improvement in the utilities’ performance. By enabling companies and regulators to identify areas for improvement, the WUSQI can support the delivery of high-quality services to customers.

5.1 Introduction

Quality is a multifaceted concept studied extensively in management and it has become critical for the success of many industries. However, due to its intangible nature, there is still a lack of consensus on its precise definition, which has evolved over time and in the literature. Quality encompasses dimensions such as performance, reliability, durability, aesthetics and customer satisfaction, making it complex and challenging to define universally. According to van Keme-nade and Hardjono (2019), quality is a “fuzzy and vague concept” that cannot be measured with certainty since it depends on individual interpretation.

Defining and measuring quality becomes even more complex when it pertains to services. Unlike products, services are intangible and their quality highly depends on the perceptions of

the users (Sousa and Voss, 2002). Public services, such as water supply and sanitation, involve multiple stakeholders with varying priorities and goals. As a result, the concept of quality in these contexts can be interpreted in diverse ways and requires careful consideration of the needs and expectations of all involved stakeholders. In such an environment where users cannot easily switch to a different service provider, maintaining high levels of quality becomes critical to protect their interests and ensure continuity of services. The lack of competition can also reduce the motivation for providers to maintain high-quality service levels, emphasising the importance of measuring quality and taking actions to ensure high-quality standards (Sala-Garrido et al., 2021). Collaboration and coordination among stakeholders are crucial to establishing clear standards for quality in public services, contributing to the well-being of society as a whole. The provision of safe and dependable water and sanitation services (WSS) is vital to safeguarding public health. To attain this objective, it is essential to prioritise the delivery of high-quality services.

Reaching a high level of service quality in the water sector requires a new management approach that ensures continuity of operations, encourages continuous improvement, develops strategic capabilities, and creates efficient and sustainable business models. To support utilities in this endeavour, the World Bank has developed the 'Utility of the Future' (UoF) programme (Lombana Cordoba et al., 2021), which aims to ignite, materialise and maintain transformation efforts in the water and sanitation sector. The UoF programme guides utilities, particularly in developing countries, to become future-focused and to provide high-quality services, by promoting best-fit practices that enable them to operate in an efficient, resilient, innovative and sustainable manner. It considers that the ultimate objective of water and sanitation utilities is to provide quality services that are reliable, safe, inclusive, transparent and responsive.

In the approach adopted by the World Bank, the quality of WSS is measured following a customer-centred perspective. Performance indicators are suggested for the individual dimensions of reliability, safety, inclusiveness, transparency and responsiveness. Based on the indicator values, the utilities are classified at world-class, well-performing, good, basic and elementary levels for each dimension. The programme proposes separate indicators to evaluate each dimension of quality of the provided services but does not recommend any method to aggregate these dimensions into a single indicator reflecting the overall quality of service levels.

In fact, composite or synthetic indicators are commonly utilised to measure the quality of services as they can effectively condense complex, multi-dimensional information and support decision-makers. Composite indicators (CIs) offer advantages such as being easier to interpret than a battery of many separate indicators. CIs are also able to track progress over time and minimise the set of indicators that need to be monitored while preserving the underlying information. However, CIs may send misleading policy messages if poorly constructed or misinterpreted (Nardo et al., 2008).

This study aims to develop a CI that reflects the quality of service provided by water supply and sanitation utilities from the customer perspective, following the UoF approach. The resulting index is named Water Utility Service Quality Index (WUSQI). Among the numerous techniques employed to build CIs, we employ the Benefit-of-the-doubt approach (BoD) popularised by Cher-

chye et al. (2007), based on Data Envelopment Analysis (DEA). This method was selected for its capability to assign weights that are the most favourable for the unit under consideration, in comparison to its peers in the sample for aggregating the various metrics. This approach mitigates potential objections from the entities being evaluated, making it a suitable approach for public services under regulation, such as water and sanitation services. The study also uses the Deck of Cards Method (DCM) (Figueira and Roy, 2002; Corrente et al., 2021), a Multiple Criteria Decision Analysis (MCDA) technique, to construct an indicator that reflects the transparency dimension of utilities' services.

The strategy developed in this study is applied to a case study of the Portuguese wholesale water and wastewater firms taking advantage of the reliable and vast data collection system provided by the Portuguese regulatory authority for this sector. To the authors' knowledge, the BoD technique has not yet been employed to construct CIs based on a customer-centred perspective of quality. The framework proposed by the World Bank in the UoF programme has not been utilised to construct CIs to express the quality of service provided by water utilities, highlighting the novelty of this research. The use of the DCM in this context represents another innovative feature of the study.

The proposed method can support regulators in evaluating water companies' performance from a customer-centred perspective, making informed decisions that positively impact service quality levels. In some countries, such as England and Wales, service quality is a key input in setting tariffs (Maziotis et al., 2017; Molinos-Senante et al., 2022a). This study can also provide valuable insights for water companies by identifying customer satisfaction factors, allowing them to improve service delivery. Overall, the relevance of the study relies on the potential to support improvements in the quality of service provided by water companies, benefiting customers and the broader society as a whole. While the primary focus of the UoF programme lies in improving water utilities in developing countries, the method is applied to a European context to demonstrate its practical relevance and applicability at a global level.

The structure of the remaining parts of this chapter is as follows: Section 5.2 provides a concise literature review. Section 5.3 outlines the methodology proposed, while Section 5.4 discusses the case study, which serves as an illustrative example of the method's strength and practical application. Section 5.5 presents and analyses the results. Lastly, in Section 5.6, the conclusions of the study are presented and potential avenues for future research are explored.

5.2 Literature Review

This section examines the literature on measuring service quality levels. Subsection 5.2.1 provides an overview of various methodologies regardless of the sector, whereas Subsection 5.2.2 focuses on the specific evaluation of service quality in the water sector.

5.2.1 Assessment of quality of services

Quality is a vital and intricate element of business strategy, impacting customer satisfaction, firm profitability and economic growth. It drives competition among firms and shapes markets, with customers seeking high-quality products and services. However, despite its significance, there is still a lack of agreement on the precise definition of quality. Reeves and Bednar (1994) suggest that instead of trying to create a single definition of quality that encompasses all the aspects of existing concepts, it is more effective to weigh the trade-offs of these definitions and select the one that best suits the practitioners' requirements. Similarly, when discussing quality definitions related to tangible products, Garvin (1984) recommends using the distinction between various quality perspectives for business advantage, ensuring that quality serves as a 'competitive weapon'.

The study by Reeves and Bednar (1994) examined the strengths and weaknesses of the different perspectives on defining quality. These include the *excellence definition*, which views quality as a higher achievement; the *value definition*, which sees quality as an added value for the organisation; the *specification definition*, which emphasises conformance to specifications; and the *customer definition*, which focuses on meeting or exceeding expectations of the customers. These perspectives are widely discussed in management literature and applied to assess and measure the level of quality of different businesses.

We summarise the strengths and weaknesses of quality definitions, according to Reeves and Bednar (1994), in Table 5.1. By examining the content of the table, we see that measuring quality as *excellence* can be challenging, while the *specification* definition primarily focuses on internal processes and may not adequately evaluate service quality. As a result, the *value* and *customer* definitions are more suitable for assessing service quality and are, indeed, the most commonly used approaches for this assessment.

Table 5.1: Strengths and weaknesses of quality definitions. Adapted from Reeves and Bednar (1994).

Definition	Strengths	Weaknesses
Excellence	<ul style="list-style-type: none"> – Strong marketing and human resources benefits. – Universally recognisable – high achievement. 	<ul style="list-style-type: none"> – Little practical guidance. – Measurement difficulties. – Rapid change of excellence attribute.
Value	<ul style="list-style-type: none"> – Multiple attributes. – Focused on internal and external efficiency. 	<ul style="list-style-type: none"> – Questionable inclusiveness. – Quality and value are different constructs.
Specification	<ul style="list-style-type: none"> – Precise measurement. – Force disaggregation of consumer needs. 	<ul style="list-style-type: none"> – Consumers do not know or care about internal specifications. – Inappropriate for services. – Specifications may become obsolete. – Internally focused.
Customer	<ul style="list-style-type: none"> – Applicable across industries. – Responsive to market changes. – All-encompassing definition. 	<ul style="list-style-type: none"> – Most complex definition. – Difficult to measure. – Customers may not know their expectations. – Confusion between customer service and customer satisfaction.

Other scholars have also been engaged in the ongoing discourse about the concept of quality, acknowledging that it is not a matter of resolution, but rather a constantly evolving idea (Golder et al., 2012; Elshaer, 2012; Kenyon and Sen, 2016). This ambiguity regarding the definition of quality has also been prevalent in the context of services. In contrast to the concept of quality used for physical products, the assessment of the quality of services (QS) places a greater emphasis on customer perception and marketing (Sousa and Voss, 2002). As Harvey (1998) points out, service quality assessment is unique to each market segment and can be classified into two main components, reflecting both the outcomes desired by the customer and the efforts that customers must undertake to achieve those outcomes. Additionally, the outcomes desired by the customer must be achieved by examining the performance of internal processes and aligning them with customer perceptions to ensure the desired outcomes are achieved. Due to the intangible nature of the service results, potential discrepancies between perception and reality are more significant in services than in goods. This fact may explain the reason why service quality has been more extensively studied in marketing than in operations, in contrast to product quality which is predominantly researched in the operations field.

Extensive literature reviews, such as Wen et al. (2022) and Zhang et al. (2021), indicate that there has been a growing focus on QS in quality management research. Numerous studies have highlighted its importance (Carnerud, 2017; Zhang et al., 2021; Lo and Chai, 2012; Sánchez-Franco et al., 2022). This trend is expected to continue in the future, potentially leading to further advancements in the field.

Prasad and Verma (2022) presented a literature review on the main methods used to measure QS and pointed out directions for future research. According to these authors, the most popular approach to measure service quality was introduced by Parasuraman et al. (1988). This scale - entitled SERVQUAL - comprises five dimensions, namely reliability, responsiveness, empathy, assurance and tangibility. The dimension of reliability pertains to the capability to provide the assured service with consistency and precision. The responsiveness dimension focuses on the promptness and willingness to assist customers. The dimension of empathy refers to the level of care and personalised attention provided to customers by the company. The assurance dimension is linked to the expertise and politeness of employees and their capacity to encourage trust and confidence. Finally, the tangibility dimension assesses physical attributes, such as equipment, facilities and the appearance of the staff. The SERVQUAL approach sees QS as the agreement between customers' expectations and their perceptions of the provided service. SERVQUAL has been vastly used in a wide range of services and has shown the potential to be applied both to private (Saleh, 1991; Reidenbach and Sandifer-Smallwood, 1990; Newman, 2001; Awasthi et al., 2011; Pakdil and Aydin, 2007; Tan and Kek, 2004; Bojanic and Rosen, 1994) and public services (Wisniewski, 1996, 2001). For reviews of this method, see Asubonteng et al. (1996) and Ladhari (2009). As noted by Asubonteng et al. (1996), while SERVQUAL is a popular tool used to measure service quality, it has been criticised for its limitations, including its assumption that customers have a clear idea of what they expect from a service and the applicability of its five dimensions to all types of services. In search of a better measure of service quality, researchers should continue to

explore alternative approaches that are more appropriate for different types of services and better capture the nuances of customer expectations and experiences.

A strong measurement strategy is essential for improving QS. Metrics communicate organisational priorities and can track progress, compare performance and identify areas for improvement. A precise measurement system for the quality of services enables early detection of deviations and highlights service improvements. Ultimately, it fosters continuous learning and growth (Harvey, 1998).

5.2.2 Assessment of quality of services in the water sector

The service quality in the water sector has been addressed in the literature under different approaches: (i) general performance assessments incorporating QS elements, following the quality-as-value definition, and (ii) QS measurement following the customer-centred perspective.

The first approach includes studies that aim to measure QS with a broader perspective, using the value definition. Although the results are often referred to as measures of service quality, they are actually reflections of overall performance levels. Such studies usually encompass customer-related measures and also integrate additional metrics that may not be directly tied to the customer's perspective, such as environmental sustainability, investment compliance, financial performance, asset management and human resources productivity.

Water services have been incorporating customer-centric aspects into their performance assessments since 1999 when English and Welsh water companies began implementing the overall performance assessment (OPA) methodology (Molinos-Senante et al., 2022a). In the literature, according to Picazo-Tadeo et al. (2008), the first paper that took a customer perspective into account when measuring water utilities' overall performance was that by Saal and Parker (2001). Since then, this strategy has been employed by several scholars (Woodbury and Dollery, 2004; Picazo-Tadeo et al., 2008; Kumar and Managi, 2010; Maziotis et al., 2017; Molinos-Senante and Maziotis, 2018; D'Inverno et al., 2021; Mocholi-Arce et al., 2021; Henriques et al., 2022; Molinos-Senante et al., 2022d; Chang et al., 2022; Duarte et al., 2009; Pinto et al., 2017a; Molinos-Senante et al., 2019; Sala-Garrido et al., 2021; Molinos-Senante et al., 2022a). Many of those works aim to produce composite indicators (CIs) usually referred to as indices of service quality. These studies are displayed in Table 5.2.

In 2008, a collaborative effort between the International Water Association and the Inter-American Development Bank resulted in the development of an initiative aimed at establishing a universally recognized model in the assessment of water utility performance. This initiative, known as AquaRating, serves as a performance system that enables the characterization and evaluation of utilities through the application of key performance indicators and the implementation of best practices. AquaRating has gained recognition as a reference model by regulators, governments, and development agencies. It encompasses eight distinct areas of evaluation, including quality of service, investment planning and implementation efficiency, operating efficiency, business management efficiency, access to service, corporate governance, financial sustainability, and

environmental management. This comprehensive approach highlights AquaRating as a system dedicated to enhancing the overall value delivered by utilities (Krause et al., 2018).

The second approach employed to address the quality of water and sanitation services (WSS) measures QS in a more focused view, using the customer definition. In this group, a prevalent method is to examine customer satisfaction, which is often achieved through surveys that employ satisfaction drivers to analyse users' perceptions of these services. This strategy was employed by Abubakar (2016) and Ohwo and Agusomu (2018) in Nigeria. Ammar and Saleh (2021) and Murrar et al. (2020) applied the SERVQUAL model in Palestine with a similar approach. SERVQUAL was also utilised by Kassa et al. (2017) in Ethiopia to investigate urban water supply services. Other studies using customer satisfaction surveys are Kumasi and Agbemor (2018), Tessema (2020), and Rustinsyah (2019). Although surveys are commonly used to collect data, they can be expensive and subjective due to challenges in designing the survey, selecting the appropriate type and method of application, and using statistical methods for analysis. For that reason, performance indicator systems have been developed to conduct QS assessments, focusing on the customer perspective.

Both value-based and customer-based approaches utilise composite indicators as a strategy to evaluate the quality of service (QS). This approach involves gathering diverse metrics from reliable sources, such as regulators or the companies themselves, and consolidating them into a composite or synthetic indicator that effectively represents the provided service quality levels. By employing this method, a comprehensive and representative assessment of QS can be achieved.

Palomero-González et al. (2022) argue that while CIs are widely used in research on services and in the water sector, they have not yet been extensively used in particular analysis of service quality under customers' perceptions. To the best of the authors' knowledge, three studies have developed CIs following the customer-centred quality concept for water utilities: Karnib (2015) in Lebanon, Molinos-Senante et al. (2017) in Chile and Palomero-González et al. (2022) in Spain. However, CIs have been developed for the same purpose under the value-based concept of quality explicitly or under the denomination of overall performance. Table 5.2 summarises the main characteristics of the studies that employ CIs to measure QS. In Table 5.2, the studies identified as adopting a value-concept of quality are the ones that incorporate at least one of the metrics not directly linked to the customer perspective. Those studies include measures of environmental sustainability, investment compliance, financial performance, asset management and human resources productivity. Developing an indicator that reflects the overall performance level of a utility may offer the advantage of being more comprehensive, which could explain the wider usage of this approach. However, it is worth noting that customer-centred approaches to measuring quality of service (QS) can be highly valuable for managers and regulators. By considering the variables that shape customers' perceptions, decision-making processes can become more informed and aligned with the needs and expectations of the users. According to Palomero-González et al. (2022), the outcomes of such assessments can significantly enhance the understanding of customers' perceived quality in an objective, quick, simple and cost-effective manner. This fact emphasises the relevance of this study.

Table 5.2: Studies with CIs to evaluate the quality of services in the water sector.

Reference	Quality concept	Composite indicator	Sample	Metrics	Method
Karnib (2015)	Customer	Quality of service index (QSI)	4 regional water authorities in Lebanon	4 metrics for 4 years: i. Network coverage ii. Water consumption iii. Continuity of water supply iv. Water quality	Fuzzy inference model
Molinos-Senante et al. (2017)	Customer	Quality of service to customers index	19 water and wastewater companies in Chile	7 metrics: i. Water supply pressure ii. Water supply quality iii. Wastewater treatment quality iv. Water supply continuity v. Wastewater collection continuity vi. Billing accuracy vii. Complaints	Ratios of Shephard's distance function to access performance changes over time
Palomero-González et al. (2022)	Customer	CI to measure the quality of water supply based on users' perceptions	32 municipalities in Valencia, Spain, receiving water from the same company	6 metrics: i. Network quality ii. Water quality iii. Water price iv. Complaints v. Inconvenience caused by upgrading the network vi. Continuity of service	MCDA model with common weights based on DEA
Duarte et al. (2009)	Value	Global index of service quality	15 water supply companies in Portugal	20 metrics from the regulator authority in Portugal grouped in 3 dimensions	Normalisation using fuzzy sets and aggregation by weighted average + Three different options are used to obtain weights from a panel of experts
Pinto et al. (2017a)	Value	QSI	99 retail water supply companies in Portugal	16 metrics from the regulator authority in Portugal	ELECTRE Tri-nC (MCDA)
Molinos-Senante et al. (2019)	Value	Synthetic index of quality of service	40 rural drinking water systems in Chile	14 metrics with weights estimated by different stakeholders	Analytical Hierarchical Process (MCDA) + Monte Carlo simulation
Sala-Garrido et al. (2021)	Value	CI of quality of service	24 water and wastewater companies in Chile	7 metrics: i. Investment compliance, ii. Investment to improve the QS iii. Network reposition iv. Non-revenue water v. Interruptions of water supply vi. Obstructions in the sewerage network vii. Payment accuracy	BoD using undesirable metrics + Nerlove-Luenberger super efficiency metric
Molinos-Senante et al. (2022a)	Value	Quality of service index	24 water and wastewater companies in Chile	10 metrics: i. Non-revenue water ii. Network reposition iii. Investment compliance iv. Water meter operability v. Interruptions in drinking water provision vi. Obstructions in sewerage network vii. Payment accuracy viii. Compliance with drinking water quality ix. Compliance with wastewater discharge x. Water supply pressure	Goal programming
D'Inverno et al. (2021)	Value	Water Utility Performance CI	93 Italian water companies	8 metrics: i. Return on assets ii. Return on Equity iii. Earnings before interest, taxes, depreciation, and amortisation margin iv. Financial autonomy v. Autonomy from third parties vi. Water losses vii. Target time to do new connections viii. Target time to repair breakdowns	BoD Model with Directional Distance Function Robust and conditional approaches
Henriques et al. (2022)	Value	Performance assessment CI	199 retail wastewater companies and 10 wholesale wastewater companies in Portugal	14 metrics from the regulator authority in Portugal	Directional BoD models for desirable and undesirable indicators

To create a CI that accurately represents service quality, one of the crucial steps is to identify the appropriate set of performance metrics that can be combined into a single index. In the water and sanitation sector, performance indicators are frequently utilised to assess various aspects of utility performance in order to identify areas that require improvement. Alegre et al. (2017) has compiled a comprehensive collection of indicators that can be used in the sector. Regulators have taken advantage of the various available metrics to better understand and support the performance of companies.

The Water and Waste Services Regulatory Authority in Portugal (ERSAR) provides one of the most widely studied sets of performance indicators in the literature. Every year, ERSAR collects a vast set of metrics from water supply, wastewater, and solid waste service providers in Portugal, and these reports can be accessed on ERSAR's website. This is part of the "sunshine regulation" policy adopted by the Portuguese regulatory authority, which involves openly publishing these metrics.

ERSAR has been reviewing and enhancing its performance indicator system over time. In 2022, the fourth generation of indicators was introduced, with the first set of results scheduled for release in 2023. The most recent data available pertains to the third generation of indicators, which covers the period spanning from 2016 to 2021. Detailed information regarding these indicators can be found in ERSAR's Technical Guide 22 (ERSAR and LNEC, 2021). ERSAR's performance indicator system for water supply and wastewater services comprises 14 primary metrics, grouped into three subsystems: (i) Adequacy of the Interaction with the User, (ii) Service Management Sustainability, and (iii) Environmental Sustainability. The first subsystem reflects the defence of user interests. The second subsystem, which reflects the sustainability of the managing entity, encompasses the economic, financial, infrastructural, operational and human resource capacity necessary to ensure regular and continuous service provision to users. The third subsystem focuses on environmental sustainability and includes aspects related to the environmental impact of the managing entity's activities, particularly with regard to the conservation of natural resources (ERSAR, 2021a).

ERSAR refers to its overall performance appraisal system as a "quality of service measurement system". However, it is important to note that the evaluation method considers various factors beyond just user experience metrics. Therefore, the approach can be characterised as a value-centred quality evaluation system, as described by Reeves and Bednar (1994).

Numerous publications have used ERSAR's data, including Duarte et al. (2009), Pinto et al. (2017a), Henriques et al. (2022), Mergoni et al. (2022), and Vilarinho et al. (2023c,d).

After selecting the appropriate metrics to be used in constructing the CI, the next step is to decide on the aggregation technique to be employed. As indicated in Table 5.2, there are various methods available for this purpose. The Benefit-of-the-Doubt (BoD) approach, which is based on Data Envelopment Analysis, has been utilised in constructing CIs in numerous fields. One of its advantages is that it allows for the assignment of specific and most favourable weights for combining the various metrics. This approach is particularly suitable for regulated markets such as water and wastewater services, where there may be disagreements among operators regarding

the relative importance of the different metrics. For this reason, the BoD technique is chosen to be employed in this study. As seen in Table 5.2, BoD models have not been used to express QS under a customer-centred perspective in water utilities, representing a novel contribution of this work.

A new approach to using performance indicators for quality of service evaluation in water and sanitation utilities has been proposed by the World Bank through its ‘Utility of the Future’ (UoF) programme. This programme was first introduced in 2021 (Lombana Cordoba et al., 2021) and was updated to version 2.0 in the following year (Lombana Cordoba et al., 2022). The UoF programme has set out ambitious objectives that comprise a complete management strategy to foster the development of the utilities and elevate WSS “beyond the next level”. The relevance and objectives of this programme are referred in page ix of Lombana Cordoba et al. (2022) as follows:

Poor service frequently stems from a vicious cycle of dysfunctional political environments and inefficient practices. Global forces—including climate change, water scarcity, population growth, and rapid urbanisation—exacerbate these challenges to providing high-quality, sustainable WSS service delivery. Therefore, WSS utilities require a new approach to planning and sequencing reforms to provide WSS services in a sustainable manner. The UoF programme provides this new approach, building on an extensive body of knowledge on utility performance improvement.

The UoF programme’s ultimate objective is to enhance and maintain the quality of services provided by water and sanitation utilities, which is the topmost priority of the management model presented by the World Bank. This quality-based management strategy requires utilities to be reliable, secure, inclusive, transparent and responsive, which are the dimensions that form the measurement framework proposed by the programme for QS evaluation. In order to be deemed reliable, utilities must provide a continuous 24/7 supply of WSS. Adherence to water and wastewater quality standards represents safety. Inclusiveness requires that no individual or group is excluded from receiving service. To be considered transparent, WSS should provide clear and accurate information regarding their finances, operations and performance. To attain responsiveness, utilities should provide clients with timely and high-quality responses to ensure their satisfaction.

The programme examines each QS dimension using one or more performance indicators, but it does not develop a CI to reflect the overall quality of WSS services. Instead, it assigns a performance level from one to five for each metric, classified as elementary (1), basic (2), good (3), well-performing (4), or world-class (5). Those values for the metric levels are averaged for each dimension, and the utility’s QS is assessed by analysing each dimension’s performance level.

The UoF programme suggests metrics that can be collected by the utilities reflecting the programme dimensions. The suggested metrics can be seen in Table 5.3.

Table 5.3: Suggested metrics in the World Bank’s ‘Utility of the Future’ (UoF) Programme to assess service quality for water and sanitation systems. Adapted from Lombana Cordoba et al. (2022)

Dimension	Metric
Reliability	Continuity (hours per day on average)
	Continuity (customers with 24/7 supply) (%)
	Availability (liters/capita/day)
	Availability of fecal sledge management emptying services (provided 24 hours after service requested) (%)
Safety	Water quality (samples meeting all standards for drinking water quality) (%)
	Wastewater and fecal sludge treatment (%)
Inclusiveness	Drinking water coverage (%)
	Sanitation service coverage (%)
Transparency	Key information disclosure (%)
	Applications of practices to generate clear information(%)
	Applications of practices for ensuring accurate information (%)
Responsiveness	Customer satisfied with service (%)
	Grievances satisfactorily resolved within seven days (%)
	Sewer blockage complaints addressed within 48 hours (%)

This study aims to propose a method to integrate the UoF programme’s dimensions into a composite performance indicator, which has not yet been addressed in the literature, representing another novelty in this work.

5.3 Methodology

In this section, the proposed methodology is described in two stages. The first stage, in Subsection 5.3.1, describes the Deck of Card Method. In the second stage, in Subsection 5.3.2, the calculation of the Water Utility Service Quality Index (WUSQI) using the BoD technique is detailed.

5.3.1 The Deck of Cards method

In this subsection, the Deck of Cards method (DCM) is presented. This method will be used as a support tool to build one of the metrics used in the QS assessment.

The DCM is a Multiple Criteria Decision Analysis (MCDA) method that has gained popularity due to its simple and intuitive approach, as outlined by Corrente et al. (2021). This method is utilised to assign values to preference parameters in MCDA models, such as the relative importance of criteria in outranking methods or values representing evaluations of alternatives on considered criteria and weights of criteria. In this study, we will describe the application of the DCM to convert a scale with various levels of criteria into a continuous interval scale, while taking into account the strength of preferences between the different levels.

As explained by Corrente et al. (2021), in the DCM, when using a discrete scale to evaluate a criterion, each level can be represented by a card that decision-makers can physically manipulate and arrange in their order of preference. The objective is to convert this discrete scale into a continuous scale usually ranging from 0 to 1. The conversion allows decision-makers to assign

numerical values that reflect the intensity of their preferences for each level. Typically, the least preferred level is assigned a value of 0, while the most preferred level is assigned a value of 1. To determine the values of intermediate levels, decision-makers must define the strength of preference between each sequential pair of levels. The interval between two consecutive levels is filled with blank cards, and the number of cards in each position reflects the relative importance of the upper level compared to the lower level. The numerical scale can now be determined by considering the total number of cards in the deck, including both level cards and blank cards.

For better clarification, let us consider an example. Suppose that the criteria E presents four levels, l_1, l_2, l_3, l_4 . The order of preference determined by the decision-makers is $l_1 \prec l_2 \prec l_3 \prec l_4$ (\prec meaning “strictly less preferred than”). The decision-makers place one blank card between l_1 and l_2 , two blank cards between l_2 and l_3 and four blank cards between l_3 and l_4 . This means that the significance of l_3 compared to l_2 is judged to be higher than the significance of l_2 compared to l_1 , and the significance of l_4 compared to l_3 is considered to be higher than the significance of l_3 compared to l_2 . The resulting deck of cards is illustrated in Figure 5.1.



Figure 5.1: Deck of Cards method (DCM) example.

In this example, if the value 0 is assigned to l_1 and 1 is assigned to l_4 , the remaining level values are given based on their position in the deck. Since there are eleven cards in the deck and ten spaces between cards, each card position is assigned a value between 0 and 1, in intervals of $(1 - 0)/10 = 0.1$. Therefore, the value for l_2 is 0.2 (since it is the third card in the deck, the value is calculated as $0 + (3 - 1) \times 0.1 = 0.2$) and the value for l_3 is 0.5 (being the sixth card in the deck, the value results in $0 + (6 - 1) \times 0.1 = 0.5$).

5.3.2 Calculation of the WUSQI using the BoD technique

This subsection explains the strategy used to calculate the CI WUSQI, which involves using a BoD linear programming model.

BoD models are DEA-based models that can handle multiple outputs representing various metrics to be aggregated and a dummy input with a unitary value for all decision-making units (DMUs). This approach was initially proposed by Melyn and Moesen (1991) to assess macroeconomic performance and popularised by Cherchye et al. (2007). The BoD model employed in this study for aggregating the chosen metrics collected from ERSAR’s data set is based on a Directional Distance Function (DDF) proposed by Zanella et al. (2015). The DDF-based BoD model can handle both desirable and undesirable metrics without requiring any adjustment of measurement scales. Desirable metrics are the ones for which a better performance corresponds to higher values. Conversely, undesirable metrics are characterised by lower values indicating better performance. The set of mathematical expressions in Model (5.1) defines the Directional Distance Function BoD model used in this study.

BoD models are used to perform a comparative performance assessment of a set of entities, commonly referred to as DMUs. To perform the complete assessment of the set of DMUs, Model (5.1) must be run and solved n times, being n the total number of DMUs. The outcomes of the model are the decision variables' values, which include v as the dummy input, and the weights u_r for the desirable metrics r , and p_k for the undesirable metrics k . The total number of desirable metrics is s , and the total number of undesirable metrics is l . The desirable and undesirable metrics are represented as y_{rj} and b_{kj} , respectively, for DMUs j (where j ranges from 1 to n). The values y_{rj_0} and b_{kj_0} correspond to the metrics of the DMU under assessment, denoted as j_0 . The index r pertains to the set of desirable metrics (with r ranging from 1 to s), and the index k pertains to the set of undesirable metrics (with k ranging from 1 to l).

$$\begin{aligned}
& \text{minimise} \quad \beta_{j_0} = - \sum_{r=1}^s y_{rj_0} u_r + \sum_{k=1}^l b_{kj_0} p_k + v \\
& \text{subject to} \quad \sum_{r=1}^s g_y u_r + \sum_{k=1}^l g_b p_k = 1 \\
& \quad \quad \quad - \sum_{r=1}^s y_{rj} u_r + \sum_{k=1}^l b_{kj} p_k + v \geq 0 \quad j = 1, \dots, n \\
& \quad \quad \quad u_r \geq 0, \quad r = 1, \dots, s \\
& \quad \quad \quad p_k \geq 0, \quad k = 1, \dots, l \\
& \quad \quad \quad v \in \mathbb{R}
\end{aligned} \tag{5.1}$$

The direction in which desired metrics expand and undesired ones contract towards the ‘best-practice frontier’ is indicated by the directional distance vector, which is specified as $(g_y, -g_b)$. The choice of the direction vector used in DEA/BoD models can impact the results obtained and has been discussed by many scholars. Depending on the objective of the study, several solutions have been proposed in the literature. Rogge et al. (2017) presents alternatives for the vector to set the directions of improvement for desirable and undesirable outputs in BoD models. In this study, we adopt the values of $(g_y, -g_b)$ as $(y_{rj_0}, -b_{kj_0})$, following Zanella et al. (2015) and Rogge et al. (2017). This approach enables each DMU to improve by following the path indicated by its specific metrics and the resulting CI value can be interpreted proportionally.

The performance level of DMU j_0 is represented by the factor β_{j_0} in model (5.1), which represents the objective of the model. The minimum value of β_{j_0} determined by optimisation indicates the maximum possible expansion of desirable metrics and contraction of undesirable metrics while satisfying the constraints in the model. This allows DMU j_0 to choose the weights that are the most favourable to it. The associated CI, $WUSQI_{j_0}$ for j_0 , is obtained as $1/(1 + \beta_{j_0})$, with a range of 0 to 1, where 1 indicates the highest level of performance. If $WUSQI_{j_0} < 1$, it

means that there is a linear combination of other DMUs that performs better overall. If $WUSQI_{j_0} = 1$, DMU j_0 is on the best-practice frontier, which implies that none of the other DMUs evaluated performs better than it does.

To limit the range of the assigned weights, weight restrictions must be incorporated into the model. Zanella et al. (2015) suggest a method for implementing weight restrictions known as AR-I restrictions, which employ virtual weights. Virtual weights in this case mean the product of each DMU's metric by its respective weight. These constraints take into account a hypothetical average DMU whose metrics are equal to the average of all values observed in the DMUs included in the sample, represented by (\bar{y}_r, \bar{b}_k) . In this strategy, percent-based constraints are formulated and included in the BoD model using the virtual weights of the average DMU. According to Zanella et al. (2015), the use of AR-I restrictions provides the benefit of being identical for all DMUs and represents the optimal choice for constructing CIs and rankings. These restrictions are the most commonly used weight restrictions in BoD models. The weight restrictions, as presented in Expressions (5.2), are included in the BoD model following Zanella et al. (2015). Lower bounds expressed as percentages (ϕ_r and ϕ_k , respectively for desirable and undesirable indicators) are employed to ensure that no weights are equal to zero, preventing any indicator from being completely disregarded in the calculation of WUSQI, and assigning a minimum level of importance to the indicator. On the other hand, upper bounds expressed as percentages (ψ_r for desirable and ψ_k for undesirable indicators) are employed to impose maximum levels of importance on the indicators.

$$\begin{aligned}\phi_r &\leq \frac{u_r \bar{y}_r}{\sum_{r=1}^s u_r \bar{y}_r + \sum_{k=1}^l p_k \bar{b}_k} \leq \psi_r, \quad r = 1, \dots, s \\ \phi_k &\leq \frac{p_k \bar{b}_k}{\sum_{r=1}^s u_r \bar{y}_r + \sum_{k=1}^l p_k \bar{b}_k} \leq \psi_k, \quad k = 1, \dots, l\end{aligned}\tag{5.2}$$

In order to evaluate the service quality of each DMU j_0 , it is necessary to solve the BoD model separately for each DMU. The resulting $WUSQI_{j_0}$ value represents the performance of the DMU in terms of service quality.

The contribution of each metric to the determination of $WUSQI_{j_0}$ represents a piece of valuable information for decision-makers. It provides crucial insights into the performance of DMUs relative to others, highlighting areas of strength and weakness. This knowledge enables decision-makers to allocate improvement efforts more effectively. The BoD technique allows extracting this information from the model results.

In standard BoD/DEA models, which are limited to analysing situations with only desirable metrics, the strengths and weaknesses of the DMUs can be identified by the magnitude of the virtual weights, computed as the values of each metric multiplied by the associated optimal weight ($u_r y_r, r = 1, \dots, s$). In these models, higher virtual weights indicate *strengths* of the DMUs, as the models assign higher weights to metrics with superior performance. Conversely, lower virtual weights indicate *weaknesses* of the DMUs, as they are assigned to metrics with inferior performance.

BoD models based on the Directional Distance Function (DDF), such as Model (5.1), include both desirable and undesirable indicators in the optimisation underlying the performance estimation. Consequently, in these models the magnitude of virtual weights cannot be interpreted directly as a sign of good performance in that dimension, as in this case a strength is signalled by high virtual weights of desirable metrics and low virtual weights of undesirable metrics.

To address this limitation, we estimate the relative strengths of the each DMU by the normalised values associated with the specification of the weight restrictions in the form of Assurance Regions type I (AR-I), as shown in (5.2). The AR-I weight restrictions are independent of the units of measurement and express in relative terms the contribution of each metric to the overall performance. Note that the denominator of these restrictions encompasses both undesirable and desirable metrics, ensuring that the sum of the relative virtual weights for all metrics results in 100%. This approach provides a suitable means to breakdown the contribution of each metric to the overall performance score. Accordingly, higher magnitude of the relative virtual bounds estimated in the optimisation process indicate strengths, both for desirable indicators and undesirable indicators ($\frac{u_r \bar{y}_r}{\sum_{r=1}^s u_r \bar{y}_r + \sum_{k=1}^l p_k \bar{b}_k}$, $r = 1, \dots, s$; $\frac{p_k \bar{b}_k}{\sum_{r=1}^s u_r \bar{y}_r + \sum_{k=1}^l p_k \bar{b}_k}$, $k = 1$).

The formulation of AR-I weight restrictions as presented in (5.2) was proposed by Zanella et al. (2015), and these authors reinforce the use of these restrictions to enable the relative importance of the metrics. However, it is noteworthy that, to the best of the authors' knowledge, the application of AR-I restrictions to express strengths and weaknesses of DMUs in DDF models has not been explored in the existing literature. Thus, this study makes a novel contribution by exploring the interpretation of by-products (optimal weights) of the performance assessment.

5.4 Case study

In this section, the data set obtained from ERSAR and the metrics chosen to compute the WUSQI are introduced in Subsection 5.4.1. In Subsection 5.4.2, the computation of the metric representing the transparency dimension for water utilities is described. In Subsection 5.4.3 the final data set for WUSQI determination is presented. Finally, in Subsection 5.4.4, the bounds used in the model's weight restrictions are determined.

5.4.1 ERSAR's data set for the determination of the WUSQI

In this subsection, the data set used in this illustrative case study is introduced and the metrics to be aggregated composing the WUSQI are presented.

The data used to compute the WUSQI was obtained from the reports issued by ERSAR for the water sector. For this study, the data set includes the entire period covered by the "third generation" of ERSAR's metrics, spanning from 2016 to 2021. In Portugal, the water sector is characterised by a division between wholesale or bulk utilities and retail utilities, each encompassing distinct management entities. Wholesale utilities primarily focus on providing services to the retail market, while retail utilities directly cater to the final users.

The study focused on the set of water wholesale utilities in Portugal that provide both water supply and sanitation services. To evaluate the performance of these distinct business areas, two separate analyses are conducted. In the study, the DMUs are defined as a combination of the utility and the year. This means that each utility can be compared with all the other utilities in the sample, as well as with its own performance in different years.

The justification for focusing on the wholesale segment in this study stems from the highly fragmented nature of the retail market, which encompasses over 200 utilities. By choosing to concentrate on the wholesale segment, with a smaller yet representative sample, the study aims to present a more thorough demonstration of the developed method's full potential. This decision enables a deeper exploration of the method's capabilities and a more comprehensive understanding of its applicability within the water sector.

The study includes the following water supply utilities: Águas de Santo André (AdSA), Águas do Algarve (AdA), Águas do Centro Litoral (AdCL), Águas do Douro e Paiva (AdDP), Águas do Norte (AdN), Águas do Vale do Tejo (AdVT), Águas do Vouga (AdVouga), Águas Públicas do Alentejo (AgDA), Empresa Portuguesa de Águas Livres (EPAL), and Infraestruturas e Concessões da Covilhã (ICOVI). AdDP was established in 2017, so data for this utility is available only from 2017 to 2021. Therefore, the total number of DMUs for the water supply sector is 59.

The wastewater utilities considered for the study are: Águas da Serra (AdSerra), AdSA, AdA, AdCL, AdN, AdVT, Águas do Tejo Atlântico (AdTA), AgDA, Associação de Municípios de Terras de Santa Maria (AMTSM), Saneamento da Península de Setúbal (SIMARSUL), Saneamento do Grande Porto (SIMDOURO), and Tratamento de Águas Residuais do Ave (TRATAVE). For AdTA, SIMARSUL, and SIMDOURO, the data available is from 2017 to 2021. Therefore, the total number of DMUs in the wastewater sector is 69.

In this study, the available metrics from ERSAR's database collected annually from Portuguese wholesale water utilities were examined. Following a thorough screening process, metrics that accurately represent the dimensions of the UoF programme were chosen. To ensure the robustness of this selection, we sought the input of experts in the water sector, with in-depth knowledge of ERSAR regulatory mechanisms.

The selected metrics are presented in Table 5.4 comprising the water supply and wastewater utilities. However, we found that there were no specific metrics available in ERSAR's data set to measure the dimension of transparency. To overcome this limitation, we elaborated a metric that captures the transparency dimension of the UoF program by using the Deck of Card method (DCM), as explained in Subsection 5.3.1. The final determination of the transparency metric is presented in Subsection 5.4.2. This approach allowed us to comprehensively evaluate the Portuguese water utilities' performance across all dimensions of the UoF program.

The Water Utility Service Quality Index (WUSQI) for the water supply business is determined by combining the metrics AA01a, AA02a, AA03a, AA04a, and AA05a, which are collected from ERSAR's data set and the new metric Transp-AA, derived from the DCM. On the other hand, the WUSQI for the wastewater business is formed by the composition of the metrics AR01a, AR02a, AR03a, AR13a, and AA04a, obtained from ERSAR's data set, and the metric Transp-AR, derived

Table 5.4: ERSAR metrics to compose the Water Utility Service Quality Index (WUSQI).

Dimension	Water Supply (AA)		Wastewater (AR)	
	Metric ERSAR	Definition	Metric ERSAR	Definition
Inclusiveness	AA01a - Service physical accessibility (%)	Percentage of the total number of households located in the area of intervention of the utility for which there are wholesale infrastructures connected or with the possibility of connection to the retail system.	AR01a - Service physical accessibility (%)	Percentage of the total number of households located in the area of intervention of the utility for which there are wholesale infrastructures connected or with the possibility of connection to the retail system.
	AA02a - Service economic accessibility (%)	Average proportion of income spent on the water supply service based on a consumption of 120 m ³ /year and an average income per household in the system's area of intervention.	AR02a - Service economical accessibility (%)	Average proportion of income spent on the sanitation service based on a consumption of 120 m ³ /year and an average income per household in the system's area of intervention.
Reliability	AA03a - Occurrence of supply failures (no./delivery point /year)	Weighted average number of supply failures per delivery point per year. The weighting factor is the number of households with effective service depending on each delivery point.	AR03a - Flood occurrence (no./100 km sewer.year)	Frequency of flooding incidents originating from the public sewer network, calculated as the number of incidents per 100 kilometres of sewer on public roads and/or properties per year.
Safety	AA04a - Safe water (%)	Percentage of water that is controlled and of good quality, determined by multiplying the compliance rate of required sampling with the percentage of compliance with the specification values set forth in the legislation.	AR13a - Effectiveness in accomplishing legal parameters of wastewater discharge (%)	Percentage of the equivalent population served by treatment facilities that ensure compliance with the discharge requirements, both in terms of periodicity of monitoring and compliance with discharge legal limits.
Responsiveness	AA05a - Reply to suggestions and complaints (%)	Percentage of written complaints and suggestions that received a written response within the legal deadline	AR04a - Reply to suggestions and complaints (%)	Percentage of written complaints and suggestions that received a written response within the legal deadline
Transparency	Indicators are not available		Indicators are not available	

from the DCM as well. In the context of ERSAR, the acronym AA refers to water supply (“Água de Abastecimento” in Portuguese), while the acronym AR represents wastewater (“Água Residual” in Portuguese).

A careful observation of Table 5.4 reveals that the metrics AA02a, AR02a, AA03a, and AR03a are the only ones that are *undesirable*, meaning that their results are better when they present lower values. This characteristic is important in the aggregation process as explained in Subsection 5.3.2.

5.4.2 Determination of the transparency metric

This subsection details how the metric to reflect transparency in the quality of services of water utilities is developed through the application of the Deck of Cards method (DCM).

The current data set of metrics gathered by ERSAR from service providers lacks a metric that represents the dimension of transparency. According to the definition of transparency provided by the UoF programme, it refers to the availability, reliability and accuracy of the information that a utility provides about its operations. To address this gap, a new metric for transparency was developed using the information contained in ERSAR’s data set.

In the data set reported from the utilities to ERSAR, a classification of the estimated reliability level for each reported metric is included, as outlined in Table 5.5. If a metric is not reported, it is indicated as “NR”. When determining a utility’s transparency level, the amount of missing data and the reliability of the reported information are both taken into account. A service provider is

considered more transparent if it reports a higher proportion of data and the reported information is more reliable.

To create a transparency scale, the DCM was utilised, as detailed in Subsection 5.3.1. The first step in this process is to define the levels of transparency in order of preference. For this study, the preferred order is straightforward: $NR \prec * \prec ** \prec ***$. The second step involves determining the strength of preference between each sequential pair of levels by placing blank cards between each pair. To ensure the credibility of this step, ERSAR's staff was consulted. Their involvement ensures the robustness of the decision-making process undertaken by water sector experts.

Table 5.5: Metric reliability in ERSAR data set. Adapted from ERSAR and LNEC (2021).

Reliability band of the Information source	Associated concept
***	Data based on extensive measurements, reliable records, procedures, investigations or analyses adequately documented and recognised as the best method of calculation.
**	Generally the same as above, but with some non-significant flaws in the data, such as some documentation being missing, old calculations, reliance on unconfirmed records, or the inclusion of some data by extrapolation.
*	Data based on estimates or extrapolations from a limited sample.

In this study, according to the opinion collected from the experts, five blank cards were inserted between the NR and * levels, three between the * and ** levels, and one between the ** and *** levels, as illustrated in Figure 5.2. Using this approach, a continuous transparency scale ranging from zero to one was obtained, with values of 0.000 for NR, 0.500 for *, 0.833 for **, and 1.000 for ***.

A new metric for transparency is then created for each reported metric, and the average of all the transparency values provided by a utility in a given year is used to determine the annual transparency metric for that utility.



Figure 5.2: Transparency metric construction via the Deck of Cards method.

5.4.3 Final data set for the determination of the WUSQI

This subsection presents the final data set comprising the metrics that will be aggregated to construct the Water Utility Service Quality Index (WUSQI).

The data sets for both groups of utilities are not always complete, as some metrics were not reported by the utilities. To address this issue, the study first attempted to use the metric reported by the same utility in the previous year, recognising that it may provide the best available representation of its performance. If the metric was also not reported in the previous year, the approach

recommended by Kuosmanen et al. (2002), Morais and Camanho (2011), and Henriques et al. (2020) was employed to handle the missing data instances, which consists of using a small value equal to the minimum value of each desirable metric as a replacement. In the case of undesirable metrics, the missing instances were replaced with a large number equivalent to the maximum value of each metric. This process ensures that the DMU's performance evaluation is not unfairly affected by the lack of data.

Due to the sensitivity of the DEA method to extreme values in the data set, outliers were replaced following the method proposed by Zanella et al. (2013). An outlier is identified, according to Montgomery (2012), as an observation that lies beyond the limits of 1.5 times the distance between the third quartile and the first quartile of the data, known as the interquartile range (IQR). Therefore, values higher than each metric's median plus 1.5 times IQR were replaced by the median plus 1.5 times IQR, and values lower than each metric's median minus 1.5 times IQR were replaced by the median minus 1.5 times IQR. This ensures that atypical observations are replaced with values closer to the centre of the distribution.

DEA formulations typically require positive inputs and outputs, although this requirement can be relaxed, as discussed by Charnes et al. (1991). In the study, the zero values were replaced with a small positive number of 0.0001, following Bowlin (1998) and Sarkis (2007).

The descriptive statistics for the metrics that compose the WUSQI are displayed in Table 5.6.

Table 5.6: Metrics for constructing Water Utility Service Quality Index (WUSQI).

Utilities' group	Dimension	Metric code	Metric description	N	Average	Standard Deviation	Minimum	Maximum
Water Supply (AA)	Inclusiveness	AA01a	Service physical accessibility (%)	59	93.47	9.03	79.00	100.00
		AA02a	Service economical accessibility (%)	59	0.18	0.05	0.12	0.28
	Reliability	AA03a	Occurrence of supply failures (no./delivery point /year)	59	0.01	0.01	0.00	0.02
	Safety	AA04a	Safe water (%)	59	99.79	0.20	99.36	100.00
	Responsiveness	AA05a	Reply to suggestions and complaints (%)	59	77.80	27.47	40.00	100.00
	Transparency	Transp-AA	Transparency metric from DCM	59	0.89	0.04	0.80	0.97
Wastewater (AR)	Inclusiveness	AR01a	Service physical accessibility (%)	69	96.17	5.32	82.50	100.00
		AR02a	Service economical accessibility (%)	69	0.19	0.09	0.02	0.37
	Reliability	AR03a	Flood occurrence (no./100 km sewer.year)	69	7.96	8.36	0.00	25.55
	Safety	AR13a	Effectiveness in accomplishing legal	69	96.21	4.32	86.50	100.00
	Responsiveness	AR04a	Reply to suggestions and complaints (%)	69	77.45	38.44	0.00	100.00
	Transparency	Transp-AR	Transparency metric from DCM	69	0.89	0.06	0.71	0.99

The study examined the correlation between the metrics utilised in building the WUSQI. The calculated Pearson correlation coefficients indicate that there is no strong relationship between the metric pairs used to construct each CI. The absolute values of the coefficients in Figure 5.3 are considerably far from one, with only four coefficients marginally exceeding 0.5. Consequently, the lack of a strong correlation provides evidence for incorporating all the variables into the models.

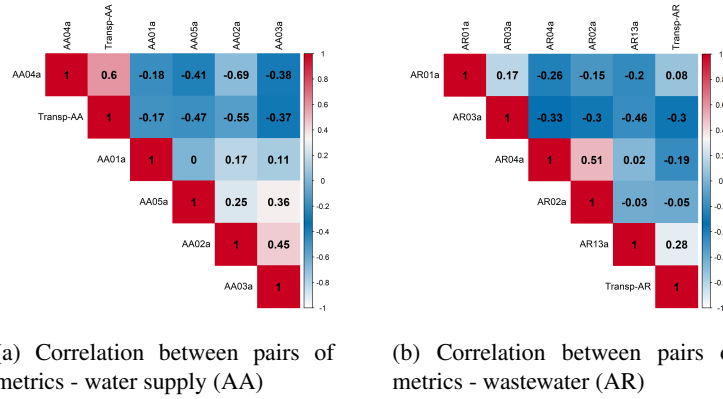


Figure 5.3: Pearson correlation coefficients between pairs of metrics.

5.4.4 Determination of bounds used in weight restrictions

This subsection details the determination of the lower and upper bounds used in AR-I weight restriction of the BoD models.

In order to solve the BoD models, it is necessary to define the lower bounds ϕ_r and ϕ_k for desirable and undesirable metrics, respectively, as well as the upper bounds ψ_r and ψ_k for desirable and undesirable metrics, respectively. These bounds are utilised in the weight restrictions, as outlined in Expressions (5.2).

The lower bounds in weight restrictions guarantee that no weights are assigned null values, thereby ensuring that all metrics are taken into account in the computation of WUSQI. This is crucial for enabling suitable discrimination of the WUSQI value because, if many weights are set to zero, a considerable number of DMUs could be considered best-performing and the comparative performance evaluation would not discriminate differences among performance levels. In this study, weight restrictions are utilised to determine the relative significance of the metrics. It is important to highlight that the lower bounds ϕ_r for desirable metrics and ϕ_k for undesirable metrics set a minimum threshold for the relative contribution of a metric. In fact, the AR-I weight restrictions in the BoD model impose that the model cannot assign weights that result in lower relative significance than those specified thresholds. Consequently, lower values of ϕ_r and ϕ_k contribute to better discrimination of lower performances of the DMUs, effectively revealing their weaknesses. However, if ϕ_r and ϕ_k are set too low, the WUSQI values may lack discrimination. Therefore, it is necessary to search for a balance that allows for both the differentiation of WUSQI values and more precise identification of DMUs' weaknesses. The lower bounds ϕ_r and ϕ_k were set to 0.05 in the study for both water supply and wastewater analysis. Different values ranging from 0.01 and 0.10 were tested. After running this sensitivity analysis, the intermediate value of 0.05 was chosen to strike a balance between the discrimination of WUSQI values and the identification of weaknesses.

The upper bounds ψ_r and ψ_k are utilised to restrict the maximum level of relative importance assigned to different metrics in the performance assessment. In consultation with experts with

extensive knowledge of regulation in the Portuguese water sector, it was determined that the specific characteristics of the wholesale market recommend that the responsiveness dimension should be given less relative importance than the other dimensions reflecting inclusiveness, reliability, safety and transparency. This is due to the limited real-time contact with the final user that occurs in wholesale water services. This decision is based on the recognition that complaints and suggestions from customers in the wholesale segment are infrequent and typically not considered critical factors for service quality assessments. Treating this dimension with equal significance as the others could potentially yield outcomes that do not accurately reflect the actual requirements for quality service in this specific market segment. Consequently, the upper bound for the responsiveness dimension, represented by metrics AA05a and AR04a for water supply and wastewater utilities respectively, was set at 0.15. This implies that the relative importance of responsiveness in the assessment ranges from 5% to 15%. In contrast, the upper bounds for the remaining metrics were not specified, indicating that the relative importance of these metrics can be greater or equal to 5%. This ensures that the relative importance assigned to these metrics remains flexible while adhering to reasonable limits in terms of the lower bounds.

By incorporating expert input and setting these upper bounds, the assessment framework achieves a balanced consideration of the metrics, taking into account the unique characteristics of the wholesale market in Portugal. This approach ensures that the evaluation remains aligned with the actual requirements and expectations for quality service in this segment.

5.5 Results and discussion

The BoD models were computed for the two different businesses, water supply and wastewater. Since the DMUs comprise a combination of utility and year, each model computation included the data for all utilities over the six years of analysis. Descriptive statistics, presented in Table 5.7, offer a summary of the obtained results. The statistics of WUSQI reveal that there is potential for improvement in both sectors. Furthermore, when examining the yearly averages of WUSQI for each year, a relative stability in the performance in both sectors is observed, indicating that the businesses have maintained a certain level of service quality over time.

Results of the WUSQI's computation, including the relative importance or contributions for each dimension, are displayed in Table B.1 (Appendix B.1) and Table B.2 (Appendix B.2) for water supply and wastewater utilities, respectively. The relative importance of the dimensions is determined by the contributions of the metrics related to each dimension. Note that the relative importance of the dimension of Inclusiveness is determined by summing the contributions of the two metrics that form this dimension.

In the following subsections, a more detailed analysis of the results is provided for each group of utilities. Specifically, Subsection 5.5.1 examines the quality of service evaluations for water supply utilities, while Subsection 5.5.2 focuses on the same evaluations for wastewater utilities. Finally, Section 5.5.3 offers insights derived from the geographical distribution analysis of both

Table 5.7: Descriptive statistics for Water Utility Service Quality Index (WUSQI).

Year	Water Supply (AA)				Wastewater (AR)			
	Average	Std. Dev.	Min.	Max.	Average	Std. Dev.	Min.	Max.
2016	0.917	0.046	0.851	0.972	0.951	0.043	0.891	1.000
2017	0.925	0.059	0.840	0.993	0.931	0.050	0.845	1.000
2018	0.917	0.067	0.840	0.998	0.926	0.049	0.836	1.000
2019	0.941	0.045	0.856	0.995	0.928	0.060	0.828	1.000
2020	0.943	0.039	0.875	0.996	0.938	0.064	0.800	1.000
2021	0.929	0.060	0.830	1.000	0.938	0.049	0.878	1.000
Overall	0.929	0.052	0.830	1.000	0.935	0.052	0.800	1.000

groups of utilities for 2021, the most recent year under examination. These insights aim to provide support for future improvement initiatives.

5.5.1 Results for water supply utilities

In this subsection, the results of the assessment for the group of utilities that provide water supply services are presented and discussed.

The evolution of the WUSQI in water supply utilities from 2016 to 2021 is depicted in Figure 5.4. It is evident from the graph that AdDP consistently outperformed all other utilities during this period. Moreover, AdDP's performance showed an upward trend over time, reaching the maximum WUSQI score of 1 in 2021, making it the only water supply utility to achieve this feat. Therefore, AdDP is an ideal candidate for identifying best practices in service quality within the sector.

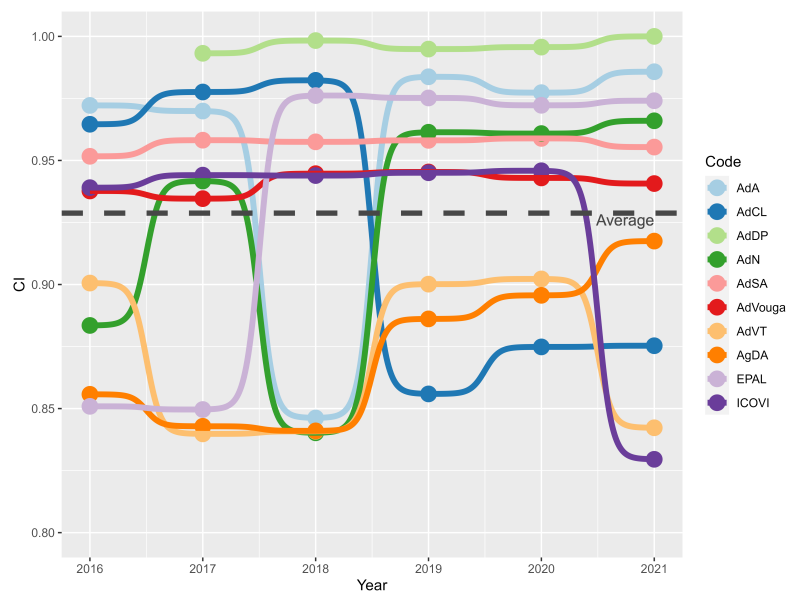


Figure 5.4: Evolution of the Water Utility Service Quality Index (WUSQI) from 2016 to 2021 in water supply utilities.

Throughout the analysis period, three utilities consistently outperformed the sector average, displaying the lowest variation in performance over the years: AdDP, AdSA, and Advouga. AdA also performed above average throughout the period, with the exception of 2018.

On the other hand, AgDA and AdvT consistently performed below the sector average, with some variation observed in both companies. Notably, AgDA displayed an upward trend in WUSQI over the past four years.

In terms of performance variation, Figure 5.4 highlights that AdCL, AdN, EPAL, and ICOVI exhibited higher fluctuations over the years. AdCL experienced a significant decline in performance in the last three years, while ICOVI's performance dropped only in the most recent year. However, AdN and EPAL managed to improve their performance and achieve relative stability in recent years.

The analysis presented in Figure 5.4 provides a comparative view of the performance variations and trends for each utility throughout the analysed period. By employing the BoD technique, the assessment highlights the strengths of each utility which minimises objections or complaints that may arise regarding the importance of the various metrics used in the evaluation. By examining the trends depicted in Figure 5.4, decision-makers can discern the utilities' performance trajectory and identify notable patterns. The graph reveals the utilities' ability to maintain or improve their standings, as well as areas where they may require additional attention.

The relative importance of each metric to utilities' performance was obtained based on AR-I weight restrictions, using the resulting weights of each metric from the computation of the BoD model. Figure 5.5 presents the importance of each dimension in the case of water supply utilities. In Figure 5.5, each utility is presented through a bar chart that showcases its performance across different years of analysis. The height of each bar corresponds to 100% total performance. Within each bar, coloured regions indicate the relative importance of different dimensions in determining the quality of service (QS) performance. By examining the size of these coloured regions, we can easily grasp the respective contributions and relative significance of each dimension to the utility's performance. Larger coloured regions within the bars indicate superior performance in the corresponding dimensions, highlighting the strengths of the utility in a given year. Conversely, smaller coloured regions in the bars signify weaknesses of the utilities in the dimensions they represent. This visual representation provides a concise and intuitive means of comprehending the impact of each dimension on the QS delivered by the utilities.

The contribution of each dimension to the QS performance of the utilities effectively highlights the strengths and weaknesses of the utilities, as evidenced by several examples. For instance, the bar chart of the top-performing AdDP utility in Figure 5.5 emphasised its inclusiveness, which remained consistently strong over the years. Inclusiveness was also the primary strength for AdSA, AgDA and ICOVI across the whole period. In contrast, for AdN, AdvT and EPAL, the dimension of safety emerges as the most significant throughout the analysed period. This finding highlights the importance placed on safety in their QS performance.

The importance of dimensions varies for the remaining utilities over the years, indicating fluctuations in areas of improvement. This variation underscores the dynamic nature of the utilities'

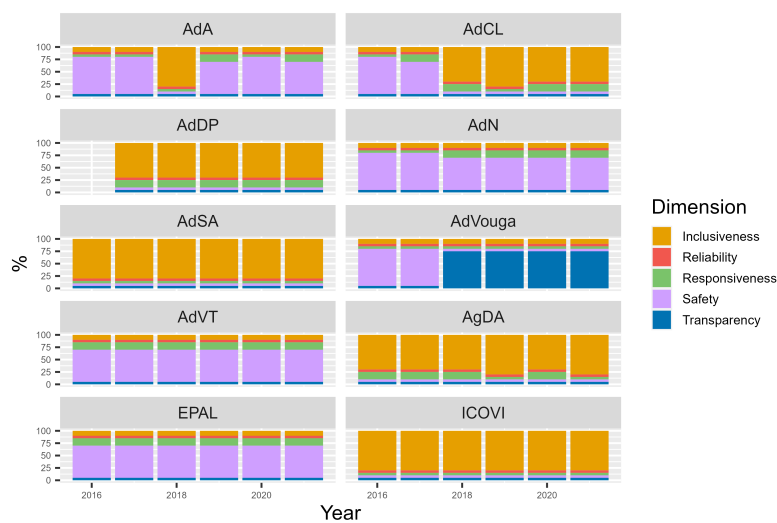


Figure 5.5: Relative importance of each dimension in the Water Utility Service Quality Index (WUSQI) - water supply utilities.

performance, with dimensions exhibiting different levels of importance at different points in time. It is worth noting that in this analysis, only one dimension emerged as a significant strength for each utility in a given year. The weaknesses of the utilities can be identified among the remaining dimensions.

Analysing this information is not always straightforward, as the contribution values in a DMU assessment are not easily comparable between different DMUs. These values represent relative importance, holding significance only for the performance of each specific DMU. We can examine the values of the safety dimension as an example of this complexity. The results of the performance metrics of the water supply utilities are displayed in Figure 5.6. A look at the graph reveals that, the safety levels, represented by the indicator AA04a (% safe water), are consistently high in Portugal. All the wholesale utilities maintained safety levels above 99% throughout the entire period. In particular, as shown in Figure 5.6, AdSA achieved the maximum value of 100% in safety for all years.

However, in the comparative analysis with other DMUs, AdSA's main strength was identified as inclusiveness in the performance assessment, rather than safety, as displayed in Figure 5.5. Furthermore, it is important to note that while AdSA performed better in terms of safety compared to other utilities such as AdVT, EPAL, and AdN, which identified safety as their main strength, we cannot definitively claim that those utilities are safer than AdSA. In fact, it can be stated that inclusiveness emerged as the strongest dimension for AdSA, while safety remained the dominant dimension for AdVT, EPAL, and AdN. Upon analysing the plots for the inclusiveness metrics, AA01a and AA02a, in Figure 5.6, it is clear that AdSA stands out as a top performer for both of them. It is important to note that while AA04a and AA01a are desirable metrics, with higher values indicating better results, AA02a is an undesirable metric where lower values indicate better performance.

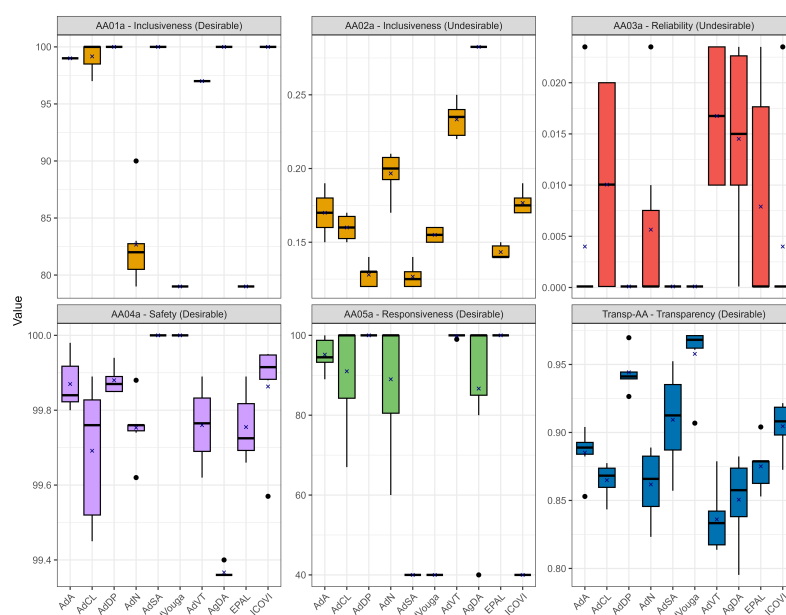


Figure 5.6: Metrics of water supply utilities from 2016 to 2021.

Lavigne et al. (2019) highlight the complexity of such comparisons, pointing out that a poorly performing DMU may exhibit a relative strength in a specific metric, which could be a weakness for a highly-performing DMU, despite the latter performing better overall in that metric.

By considering both the importance of dimensions and the results of the WUSQI, utilities can pinpoint areas that require improvement and make informed decisions to enhance their overall service quality. A notable example is ICOVI's decline in performance in 2021, where decision-makers should concentrate on addressing identified weaknesses. In this specific case, a closer examination of metric values reveals a significant deterioration in ICOVI's reliability. Specifically, the number of supply failures per delivery point (AA03a) reached the highest level within the entire sample, indicating the worst performance in this regard. This clear indication highlights a critical area for ICOVI to prioritise and improve upon. The radar chart shown in Figure 5.7 provides a visual representation of ICOVI's metrics in 2021, as well as the sector's average for the same year. These metrics have been normalised on a scale that considers the sector's average as 100 to ensure comparability. Notably, the undesirable metric AA03a demonstrates a significantly poorer performance compared to the sector's average in the same year.

One important aspect to consider when analysing the presented results is the role of the regulator in suggesting continuous improvement actions for the utilities. Based on the performance of each utility in different dimensions, the regulator can provide guidance to companies on how to improve their service quality. For instance, for utilities that consistently underperform in specific metrics, the regulator can provide targeted support to address the issue. This could include setting specific targets for improvement, technical assistance or even imposing fines for non-compliance. On the other hand, for utilities that excel in certain dimensions, such as AdDP in inclusiveness, the regulator can recognise their success and encourage them to share their best practices with other



Figure 5.7: Comparison between the performance of ICOVI and the average performance of the sector in all metrics for 2021

utilities.

5.5.2 Results for wastewater utilities

This subsection displays and discusses the results of the assessment for the group of utilities that provide wastewater services.

Figure 5.8 illustrates the progression of the WUSQI in wastewater utilities between 2016 and 2021. In this analysis, ten DMUs emerged as top performers, achieving the highest WUSQI score of 1. Notably, each year included in the analysis featured its own set of top performers. In 2016, AMSTM and AdSA stood out, followed by AdSA in 2017, AdSerra in 2018, AdSA in 2019, and both AdVT and SIMDOURO in 2020. Lastly, in 2021 AMSTM, AdSerra, and TRATAVE claimed the top spot in 2021. These utilities' metrics for quality of service in those years can serve as benchmarks for the wastewater sector. Additionally, AdSerra, AdVT, SIMDOURO and TRATAVE consistently performed above the sector's average throughout the entire analysis period. On the other hand, AdA, AdN, AgDA, and SIMARSUL, consistently fell below the sector's average. The other utilities exhibited more variability in their performance across the period.

The visualisation presented in Figure 5.8 proves to be a powerful tool for detecting significant changes in performance. It enables the identification of utilities that have achieved relative stability over time, exemplified by AdSerra, which consistently maintained a WUSQI value between 0.992 and 1.000. On the other hand, it also highlights utilities that have experienced remarkable variations, such as AMTSM. By closely examining and analysing these variations and trends, decision-makers can gain valuable insights into the underlying factors driving performance fluctuations within the utilities. These insights can inform strategic decision-making processes, allowing for targeted interventions and improvement initiatives where they are most needed.

In the context of wastewater utilities, Figure 5.9 displays the relative importance assigned to each dimension based on their respective metrics, which can be interpreted in the same way as in the water supply sector.

By examining the bar charts, we can gain insights into the relative importance of various dimensions in the quality of service (QS) performance of different utilities across different areas.

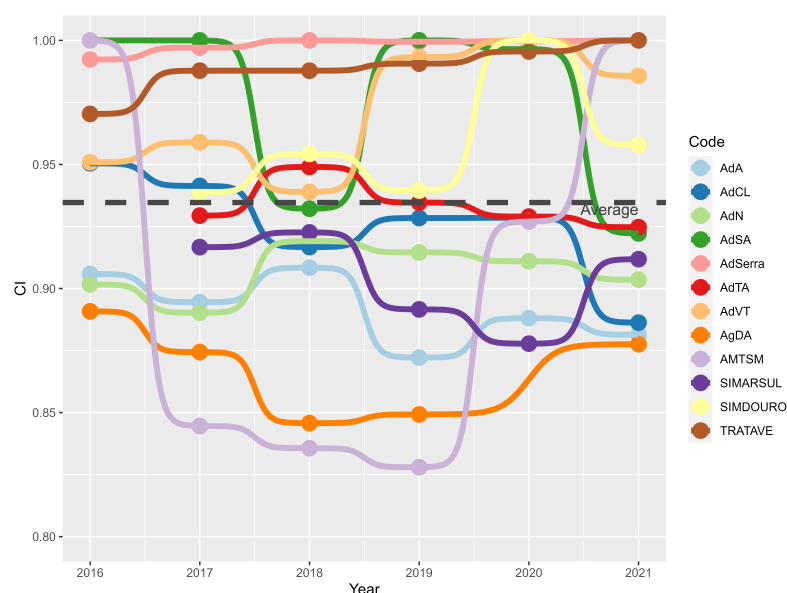


Figure 5.8: Evolution of the Water Utility Service Quality Index (WUSQI) from 2016 to 2021 in wastewater utilities.

AgDA, AMTSM and SIMARSUL, for example, exhibited consistent strength in inclusiveness throughout the entire analysis period. On the other hand, AdN and SIMDOURO consistently showcased strong safety as their most significant dimension across all the years under evaluation. The other utilities, however, demonstrated more diversity in their primary strengths.

Notably, in the case of wastewater utilities, multiple strengths were identified in each utility for a particular year, which distinguishes them from the water supply sector. For instance, in 2021, AdSerra showcased a relative importance of 38.97% in reliability, making it its major strength for that year. This utility was also strong in inclusiveness that accounted for 35.10% of the relative importance in this year. Transparency accounted for 15.83%, and responsiveness and safety for 5.09% and 5.00%, respectively. These figures reveal the main weaknesses for AdSerra in 2021, as safety and responsiveness scored relatively lower compared to the other dimensions. Therefore, AdSerra should prioritise improvement actions aimed at addressing these weaknesses.

To gain a deeper understanding of the wastewater utilities' results, it would be worth examining the factors that contributed to the top-performing utilities' success. Specifically, investigating the specific policies or practices that the top performers implemented to reinforce their strengths and achieve the highest WUSQI scores could provide valuable insights. If commonalities among these utilities are identified, they could be replicated by other wastewater utilities to enhance their service quality.

Furthermore, it would be advantageous to investigate the variations in the performance of other utilities and determine the factors that contributed to their inconsistent service quality, such as the weak reliability levels of many of the low-performing wastewater utilities. It is possible that external factors, such as severe weather events like heavy rainfall, may have influenced the reliability metric, which is linked with flood occurrence in wastewater systems. Moreover, internal factors

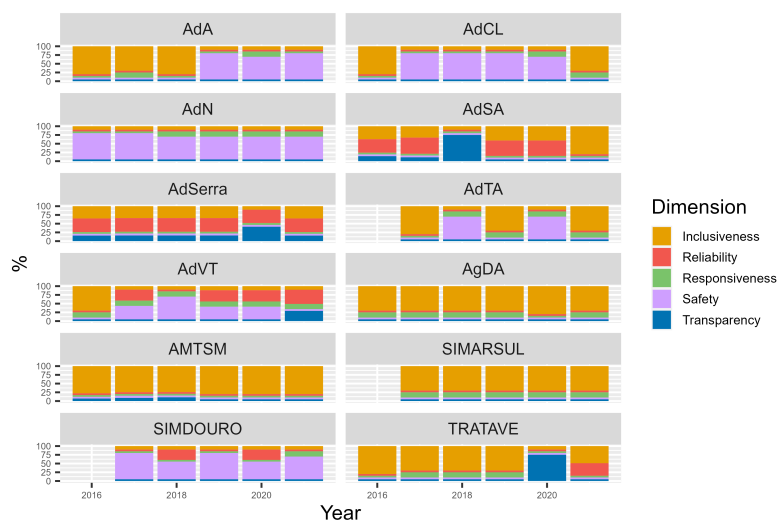


Figure 5.9: Relative importance of each dimension in the Water Utility Service Quality Index (WUSQI) - wastewater utilities.

like management practices and resource allocation could have also impacted their performance.

Regulators can identify best practices and areas for improvement by analysing the top-performing and bottom-performing utilities, as well as those with more variability in their performance. This analysis can inform the development of policies and guidelines that promote continuous improvement in service quality across the wastewater sector.

5.5.3 Geographical distribution insights comparing water supply and wastewater utilities

This subsection provides additional insights into the assessment results by highlighting the geographical distribution of the water utilities. Specifically focusing on the year 2021, the analysis combines both groups of utilities, aiming to support future improvement initiatives.

In Figure 5.10, the maps depict the locations of each utility's headquarters along with their evaluation results for the latest year of analysis, 2021. The symbols used in the maps represent different performance levels: a star indicates top-performing utilities, a top-pointing triangle represents utilities performing above average except for the top performers, and a bottom-pointing triangle represents utilities performing below average. Additionally, the colour of each symbol signifies the dimension in which the utilities excel, reflecting their main strength.

The results of the most recent year analysed reveal that inclusiveness and safety are the predominant strengths among utilities in Portugal. Additionally, six companies, namely AdA, AdCL, AdN, AdSA, AdVT, and AgdA, operate in both the water supply and wastewater sectors. Remarkably, five of these companies consistently excel in the same strength for both water supply and wastewater services. Specifically, AdCL, AdSA, and AgdA demonstrate a strong emphasis on inclusiveness, while AdA and AdN prioritise safety as their main strength. As these companies operate in both water supply and wastewater segments, it can be inferred that there is a consistent

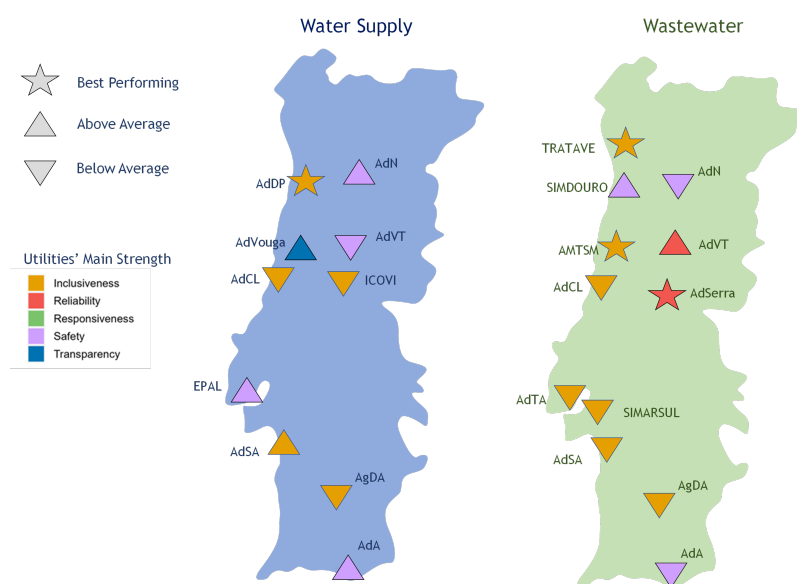


Figure 5.10: Results for Water Utility Service Quality Index (WUSQI) assessment in 2021.

approach to management practices across both areas. This alignment in priorities may indicate a deliberate and strategic focus on inclusiveness and safety throughout their operations. Such consistency in managerial practices across sectors reflects a shared commitment to excellence and suggests the presence of effective strategies in place to address these key dimensions.

5.6 Conclusion

This study proposes the Water Utility Service Quality Index (WUSQI) as a composite indicator that reflects the quality of service provided by water supply and sanitation utilities from a customer perspective. The WUSQI rests on the framework introduced by the World Bank's 'Utility of the Future' (UoF) programme, which aims to reflect the reliability, safety, inclusiveness, transparency and responsiveness of the services offered by water sector companies. The Benefit-of-the-Doubt (BoD) approach, based on Data Envelopment Analysis (DEA), is employed to assign weights for aggregating various metrics. The Deck of Cards method (DCM), a Multiple Criteria Decision Analysis (MCDA) technique, is used to define the transparency metric, which was not available in the examined data set.

We apply the WUSQI to assess the quality of Portuguese wholesale water and wastewater firms and find that it is an effective tool for performing a quality service level benchmarking exercise and uncovering performance trends over time. While the UoF programme was originally designed to address water sector needs in developing countries, this study showcases its applicability in a European context, specifically within the water sector of Portugal. By selecting Portugal as a case study, the study highlights the method's capabilities and its relevance in assessing service quality in a developed country setting.

The study's findings have significant implications for the water supply and sanitation sector, where measuring and ensuring high levels of service quality is crucial for public health and well-being. The WUSQI can help utilities and regulators identify strengths and weaknesses, set targets and track performance over time. By adopting a customer-centred perspective and measuring quality along multiple dimensions, the WUSQI encourages utilities to improve their services continuously and to foster trust and satisfaction among customers. Compared to value-centred broader approaches to determining service quality, the WUSQI's focus on the customer perspective represents a significant advantage in terms of enhancing the knowledge of customers' perceived quality in an objective and effective way.

This study makes several innovative contributions to the literature. First, it applies the BoD technique to measure the service quality of water utilities from a customer perspective. Moreover, the AR-I weight restrictions in the BoD model are utilised to reveal the relative importance of the various dimensions. The study also uses the UoF framework as a basis for developing the methodology, which is a novel application of this framework. Finally, the study develops a transparency metric by utilising the DCM method with the data set provided by ERSAR.

One notable strength of this study is the integration of expert opinion in key stages of the methodology, such as the definition of metrics and the construction of the transparency metric using the DCM. This inclusion of expert input enhances the applicability of the study to the context of water wholesale utilities in Portugal. By incorporating expert knowledge and insights, the study benefits from a comprehensive understanding of the industry and can provide more accurate and meaningful results.

One limitation of the study is that it does not consider the diverse environments in which utilities operate. The regulator may need to take this into account when analysing the results and developing improvement strategies for the utilities. Additionally, changes in the regulatory framework or in the market conditions may also affect the performance of the utilities. Introducing contextual variables into the model could provide more insights into the utilities' performance and address this limitation.

Subsequent studies could also focus on the group of utilities that operate retail systems that are closer to end-users. Analysing the performance of these utilities would provide valuable insights into the specific challenges and opportunities they face in delivering water services directly to consumers, thereby complementing the findings of this study focused on wholesale utilities.

In conclusion, the WUSQI represents a valuable tool for assessing and measuring the quality of water supply and sanitation services, thereby contributing to the water sector's improvement and the achievement of the Sustainable Development Goals. The study's relevance lies in its emphasis on the importance of adopting a customer-centred approach to service quality measurement, which encourages further research on the subject, especially in the context of other public services. It is expected that the WUSQI fosters collaboration and coordination among stakeholders, leading to the provision of high-quality and reliable water and sanitation services.

The measurement of asset management performance of wholesale water companies

This chapter aims to present innovative methods to enhance the knowledge on asset management practices in the water sector, by exploring the performance of Portuguese water supply companies operating in the bulk market. Two Benefit-of-the-Doubt (BoD) Composite Indicators are developed to highlight different aspects of asset management approaches. The first reflects organisations' performance in maintaining their infrastructures at acceptable operational levels, and the other reveals their maturity in asset management practices. Robust and conditional approaches for estimating the BoD indicators are applied, allowing to obtain results that account for the effect of contextual variables on companies' performance. Additionally, the performance of the companies is analysed over a 5-year period. The results show that there is significant room for improvement given the indicators' values estimated in the benchmarking analysis. The type of management systems and areas of intervention (urban, semi-urban or rural) are factors that present significant impact in asset management performance. The analysis of trends in the evolution of performance over time revealed improvements both in the companies' managerial practices and operational results.

6.1 Introduction

Sustainability can be defined as development that “meets the needs of the present without compromising the ability of future generations to meet their own needs” (Brundtland, 1987). This notion entails balancing three key interconnected factors: economic growth, social inclusion, and environmental preservation. Water availability and its associated services substantially impact all of these elements, making water essential for supporting economic activity, improving societal well-being, and protecting the environment (Connor, 2015). Goal 6 of the United Nations' Sustainable Development Goals (SDGs) is to “ensure the availability and sustainable management of water and sanitation for all”. This goal is closely interlinked with the other SDGs, which demands a structured strategy for managing the resources required to meet the intended targets associated with SDG 6 (Hall et al., 2016).

The infrastructures designed to provide water services demand special attention due to the serious consequences in case of failures or leakages. A simple water main break can lead to damages or failures to adjacent infrastructures, such as roads, oil or gas distribution systems, besides the direct effects of water supply shortages (Mazumder et al., 2018). Under the framework of asset

management, organisations can employ an integrated strategy to ensure that assets will fulfil the intended goals. According to the United Nations Technical Committee for Asset Management Systems (TC-251), asset management represents a key enabler contributing to the achievement of SDGs by organisations. Consequently, there is a natural alignment between asset management and the desires represented in the SDGs (ISO/Technical Committee 251, 2018), which is specially important in what concerns public service utilities, such as water, gas and electricity companies.

Asset management is defined by ISO 55000 as a “coordinated activity of an organisation to realise value from assets”. By covering strategy, safety, environment, cost, risk and life cycle, this approach represents more than an extension of maintenance. Value realisation entails balancing costs, risks, opportunities, and performance rewards. However, the concept of value will vary depending on the demands of each organisation and its stakeholders (ISO, 2014a). ISO 55001:2014 (ISO, 2014b) is the international standard that specifies the requirements for an organisation to develop an asset management system including a comprehensive set of tools, rules, processes, and information systems to ensure that the management objectives are satisfied.

According to Luís and Almeida (2021), the adoption of asset management strategies in the water sector was triggered by different reasons around the world. The regulation was the primary motivator in the United Kingdom, whilst in Australia and New Zealand the first issue was maintenance optimisation. In the United States and Canada, the critical issue was concerned with asset ageing and deterioration, while in the Netherlands, the emphasis was on establishing and ensuring service levels.

In the first decade of the twenty-first century, the concept of asset management began to be internalised in the water sector in Portugal. Despite the significant involvement of the leading agents, the results of the dissemination and application of asset management are not yet visible in a uniform manner in the national panorama (Luís and Almeida, 2021). The water, wastewater and solid waste services are overseen in Portugal by ERSAR, *Entidade Reguladora dos Serviços de Águas e Resíduos*, the sector’s regulatory authority. ERSAR’s monitoring process relies on the comparison of operators based on performance indicators that are made public. This practice, known as *sunshine regulation*, has successfully encouraged performance improvement in the sector, praising good practices alongside exposing companies to “embarrassment” for bad performance (Marques and Pinto, 2018).

The extensive set of indicators requested annually by ERSAR to the sector’s operators allows the analysis of companies’ performance in multiple facets. This study explores asset management practices by selecting and analysing the metrics collected by ERSAR and which are clearly related to that field to perform benchmarking. More specifically, this study is focused on Portuguese water supply companies operating at the bulk level and evaluates performance trends from 2016 to 2020.

The information provided by ERSAR is used to construct composite indicators (CIs) that aggregate the selected metrics to obtain a summary measure that incorporates multiple dimensions. The technique utilised to build the CIs is the Benefit-of-the-Doubt approach (BoD), popularised by Cherchye et al. (2007) based on Data Envelopment Analysis (DEA) models. The BoD method was chosen for its ability to estimate the most favourable weights for the unit under consideration

when compared to the peers in the sample, so no water company can object to those weights, making this strategy appropriate for sunshine regulation purposes. The robust and conditional formulations in the BoD approach are employed to overcome the effect of outliers and to assess the influence of the environment on companies' performance. A novel visualisation framework for the assessment of companies' performance is also presented.

Benchmarking studies using data collected by regulatory bodies are common in the literature. However, to the best of our knowledge, there are no benchmarking studies using those data with a specific focus on water system's asset management. In summary, this work aims to fill this literature gap by developing two complementary composite indicators focused on asset management performance (namely, the *Resource and Infrastructure Sustainability Index* and the *Asset Management Maturity Index*). The practical relevance of the proposed approach is demonstrated using the information collected by ERSAR to compare the bulk water supply companies operating in Portugal in the period from 2016 to 2020. This period corresponds to the most recent ERSAR's framework described as "third generation of indicators". The composite indicators developed in this work are used to compare the performance of different companies in a given year (a cross sectional approach), as well as to reveal performance trends over a five-year period. This novel evaluation method using ERSAR's data with focus on asset management represents the innovative contribution of this study.

The relevance of this study is justified by the urgent need to establish improvement processes in the management of assets at water systems. Sustainability is a major driver for enhancing water distribution system management. Water is a crucial resource for human life and according to Vieira et al. (2020b), 30% to 40% of treated water is lost worldwide due to degradation of water system infrastructures. Water and wastewater systems are deteriorating all around the world. Furthermore, because the water sector is capital intensive, and infrastructure expenditures are intended to last for a long time, physical asset management must be particularly efficient. According to Marlow and Burn (2008), efficient asset management requires the appropriate selection of metrics related to the inputs and outputs. Monitoring key performance indicators must be an effective practice, capable of providing feedback on the implementation of strategies, in order to guide decision-making and promote improvements in the sector.

The remaining parts of this chapter are structured as follows: section 6.2 presents a brief literature review, an overview of the water sector in Portugal is discussed in section 6.3, the proposed methodology is explained in section 6.4, the case study is detailed in section 6.5, section 6.6 discusses the results, and the conclusions are presented in section 6.7.

6.2 Literature review

The literature review presents the approaches available for benchmarking in the water sector in subsection 6.2.1, and subsection 6.2.2 discusses the use of performance measurement techniques in the field of asset management.

6.2.1 Benchmarking approaches using performance indicators in the water sector

The concept of benchmarking or relative performance assessment implies a systematic comparison between similar entities, known as Decision Making Units (DMUs). Examples of entities that can be considered as DMUs include groups of companies, organisations, countries, projects, among others. The main objective of a benchmarking approach is to foster performance improvement, which can happen implicitly by drawing the attention of DMUs to the issues highlighted in comparative studies. However, more explicitly, benchmarking may lead to incentives or rewards for the DMUs under evaluation, in the form of salary plans, tariff regulations or budget rules. This practice is especially useful when applied in monopoly regulations (Afsharian et al., 2022). Benchmarking practices can also help in conflict resolution by redirecting the focus of stakeholders to performance improvements (Berg, 2007).

Marques and De Witte (2010) describe the benefits of benchmarking public service activities. These authors highlight two different perspectives applied in benchmarking approaches: i) metric benchmarking, which allows organisations to evaluate performance and compare it with competitors, and ii) process benchmarking, where the companies map their internal processes and look for best practices in the industry to enable superior performance. In that sense, metric benchmarking identifies *what* to improve, whereas process benchmarking emphasises *how* to improve. However, in many cases, because different companies do not typically share information about their performance among themselves, benchmarking studies can only be conducted with the involvement of regulatory entities, who receive data from companies that operate in natural monopoly contexts. To this extent, the aim of the regulators is to stimulate, support and monitor benchmarking processes among organisations, set rules and standards of comparison, collect and publish results, and find out *where* to improve. This process can contribute to identify best practices and guide the design of strategies for improvement.

Regulators seek to create a pseudo-competitive environment, which stimulates companies to raise their efficiency levels and reduce their prices (Heesche and Asmild, 2022). Independent regulators have legislative, executive, and judicial authority to monitor several operators by enforcing the required regulations. The governance system of regulators is discussed by Marques and Pinto (2018), emphasising their independence and responsibility, the interaction with policy-makers, operators, and customers, as well as their internal processes including judgement criteria and transparency. Those authors conclude that deficient governance systems may lead to excessive governmental influence in regulator's activities impacting their transparency and accountability.

The governance model that became prominent in the recent decades, known as yardstick competition, reinforces the comparison of the regulated firm's performance with that of other firms in the same sector (Marques, 2006). Benchmarking instruments applied by the regulator are always included in the various types of yardstick competition. The incentive for the operators to improve their efficiency comes from the information received from other firms so that the regulatory process becomes an artificial competition process among them. Marques (2006) explains that there are two main approaches in yardstick competition. The first strategy, which often has more au-

thoritarian characteristics, uses benchmarking to set pricing and decide the operators' tariffs. It is known as *price yardstick competition*. In contrast, the second one, known as *sunshine regulation*, represents a lighter variant of yardstick competition and includes a comparison and public debate on the operators' performance.

In water utilities, regulators perform a macro or top-down benchmarking to get information about the operators' level of performance and set policy targets for the sector. At the same time, the companies themselves use bottom-up benchmarking, looking at their performance to perform a diagnosis and identify areas or activities to improve (Marques and De Witte, 2010).

Performance indicators can be used to perform benchmark analysis at different levels, and global measures of efficiency are commonly employed by regulators to get information about the operator's performance. They are usually employed as decision support tools to prioritise improvement actions and analyse the effect of previous measures (Vilanova et al., 2015). The use of indicators for performance benchmarking has become a crucial strategy to promote improvements within the water sector (Henriques et al., 2020). For an comprehensive discussion about the choice of indicators in the water sector, see Vilanova et al. (2015) and Alegre et al. (2017).

Models based on Data Envelopment Analysis (DEA), originally developed by Charnes et al. (1978), represent very useful tools to support benchmarking processes. Non-parametric techniques such as DEA differ from methods that employ production functions with theoretical imposed functional forms or engineering standards. DEA is a data-driven non-parametric method that assesses performance against the best practices observed in a set of DMUs (Afsharian et al., 2022).

In a literature review covering 190 studies on water services performance published between 1969 and 2008, Berg and Marques (2011) report that 34% of the studies reviewed use non-parametric methods and, among them, 72% apply DEA. In a more recent review, Goh and See (2021) confirm the interest in DEA methods in water sector research, since the term "DEA" represents 33.80% of author's keywords used among the studies reviewed that were published from 2000 to 2019. Several benchmarking works applying DEA have dealt with the efficiency of water systems worldwide: Thanassoulis (2000a,b) and Walker et al. (2019) in United Kingdom, Byrnes et al. (2010) in Australia, Wang et al. (2018) in Canada, Berg and Lin (2008) in Peru, Alsharif et al. (2008) in Palestina, Dong et al. (2018) in China, Marques et al. (2014) in Japan, Lo Storto (2018), D'Inverno et al. (2021) and Romano and Guerrini (2011) in Italy, among others. Bogetoft (1995, 1994) developed techniques based on DEA to deal with the regulatory agencies' incentive mechanisms. Those incentive schemes were also addressed in a cross-country study performed by De Witte and Marques (2010a) that compared the water sector from the Netherlands, England and Wales, Australia, Portugal and Belgium. The results suggest that the incentives have positively impacted the sector's efficiency. In a specific study that examines the adoption of the sunshine regulation in the Netherlands, De Witte and Saal (2010) describe the effectiveness of this approach examining data from different periods before and after the employment of sunshine regulation, by using DEA methods. Those authors conclude that the adoption of sunshine regulation beneficially resulted in higher productivity, that was transferred to customers as price reductions.

Techniques based on DEA may also be employed for the construction of composite indicators

(CIs). CIs entail the combined analysis of a set of performance indicators to compare multiple-dimensional activities. According to Vilanova et al. (2015), even though the collection of data and generation of multiple indicators represent a complicated process, the aggregation of those indicators into an overall measure of performance may be even more challenging involving creativity and experienced judgement. The use of a method based on DEA presents the advantage of being data-driven, avoiding the extensive interaction with stakeholders to decide the relative importance of indicators. This strategy known as the “Benefit-of-the-Doubt” (BoD) approach overcomes the concerns about the need for normalisation and identification of “right” weights, allowing an easy and intuitive interpretation of results (Cherchye et al., 2007; Nardo et al., 2008). BoD models were initially proposed for macroeconomic performance assessment (Melyn and Moesen, 1991) and have been extensively applied in many areas such as transportation (Gruetzmacher et al., 2021), competitiveness (Bowen and Moesen, 2011; Lafuente et al., 2020), human development (Rogge, 2018; Van Puyenbroeck and Rogge, 2020), quality of life (Morais and Camanho, 2011), social inclusion (Verbunt and Rogge, 2018), public health (Pereira et al., 2021), environmental performance (Zanella et al., 2013), and active ageing of population (Amado et al., 2016).

The standard DEA models, including BoD, present the inconvenience of being too sensitive to outliers and not allowing statistical inference. Several approaches have been proposed in the literature to tackle these issues. For example, detection outlier procedures or *robust* approaches have been introduced to mitigate the impact of outlying observations (see all the discussion in Henriques et al., 2022). In addition, *one-stage* or *two-stage* approaches have been suggested to investigate the influence of external conditions on the efficiency estimates (see for example De Witte and Marques, 2010b; Bădin et al., 2014). In this vein, the works of Henriques et al. (2020); Molinos-Senante et al. (2015); Dong et al. (2017); Romano and Guerrini (2011) applied DEA methods to evaluate water systems.

An alternative method was developed by Daraio and Simar (2005, 2007a) to compute conditional scores while accounting for the influence of external factors directly in the efficiency score estimation (*conditional* approach). Then, the influence of exogenous variables on the performance is estimated using a smoothed non parametric regression between the ratio of conditional and unconditional efficiencies. However, those studies allowed the appraisal of the context factors using only continuous variables. De Witte and Kortelainen (2013) introduced the use of both continuous and discrete variables as external factors. Since then, many studies have adopted that approach for evaluating water systems, such as De Witte and Marques (2010a), Marques et al. (2014), D’Inverno et al. (2021), Mergoni et al. (2022).

In the literature review issued by Berg and Marques (2011), about 35% of the non parametric studies analysed the context of water utilities using explanatory exogenous factors, and more than twenty different variables were identified as being used in those studies. Those exogenous variables include customer density, proportion of non-residential customers, peak factor, and water losses. Tourinho et al. (2022b) presented an overview of the contextual variables used in studies that deal with performance of water supply systems. According to those authors, the most frequent contextual variables used in the literature are: ownership, regional differences, scope of services,

customer density, population density, water source, water losses and peak factor (ratio between the highest and the average water consumption within a month).

6.2.2 Performance measurement in asset management

Indicators are frequently used to measure performance and make decisions in asset management. At the strategic level, an asset management system emphasises key performance indicators in conformity with higher-level objectives. By doing that, the alignment between asset management objectives and business objectives can be pursued (Gavrikova et al., 2020). Galar et al. (2014) and Cecconi et al. (2019) discuss the popularity of indicators as decision-making tools for asset management. The selection of the most suitable performance indicators for asset maintenance was addressed by Gonçalves et al. (2015), and Dutuit and Rauzy (2015) analysed ‘importance measures’ applied to complex components. Attwater et al. (2014) investigated the state of play of performance measurement for asset management systems. Their findings revealed that it is still an unsettled issue how to measure the performance of asset management systems. Further research is needed to understand the linkage between organisation performance, asset performance and asset management performance.

Galar et al. (2014) compares the use of individual indicators versus aggregated metrics in the form of composite indicators to measure asset management performance. At the core of this discussion, there is the possible loss of information that arises when aggregating many indicators and the resulting misconception or misunderstanding of the actual phenomenon. This idea is counter-balanced by the fact that an aggregate indicator can be more intuitive and simpler to communicate for managers. For this reason, in asset management, weight summations using aggregating weights provided by specialists are the most frequently used, even though direct ratios between pairs of indicators are also frequently employed (e.g., the maintenance cost divided by the asset replacement value). Statistical techniques can also be used to perform aggregated metrics. Galar et al. (2014) also highlight the use of some statistical techniques such as principal component analysis (PCA) in setting suitable weights. Other types of aggregation strategies found in the literature are the fuzzy logic (Jasiulewicz-Kaczmarek and Żywica, 2018; Famurewa et al., 2014) and Analytical Hierarchical Process (AHP) (Hassan and Khan, 2012). To our knowledge, asset management performance at the corporate level has not been measured using composite indicators based on BoD and it is therefore the object of this work. Due to the complexity of this subject and the many dimensions involved, a vast unexplored area of research exists (Galar et al., 2014).

6.3 The water sector in Portugal

In recent decades, Portugal has gone through substantial changes related to water supply services, mainly concerning service access, quality of service and structure of the market. Before 1993, the public sector had full ownership of water services. That was modified by Executive Law No. 372, which promoted the water sector restructuring, allowing the private capital to participate in the sector and establishing a regulatory authority to deal with water services. Since this period the

service coverage increased from 81% to 96% and the acceptable level of water quality raised from 50% to 99% (Marques and Simões, 2020).

In the Portuguese water sector, the national regulatory agency, ERSAR, specifies a set of key performance indicators and collects data for each operator. Following the sunshine regulation approach, the results are publicly disclosed. The powers of ERSAR are not coercive, and the regulator does not actively engage in the pricing formulation process (Gonçalves et al., 2014).

Another consequence of the updated water sector organisation after 1993 is the separation between bulk or wholesale systems and retail systems, which occurred both in the water and wastewater businesses (Marques, 2008). The water supply wholesale companies are responsible for water abstraction, treatment and storage before distributing the water to the retail companies that supply water to end-users.

Portuguese water companies can currently be managed according to three different models, namely direct management, delegation and concession. In the direct management model, municipalities, municipal services and associations of municipalities own and operate the water services, usually without participation of private companies. The delegation model works with a municipal company or a company established in partnership with the State (municipal or state company), parishes, or user associations. In the delegation system, the company is owned and controlled exclusively by the State (central, municipal or both), without a contract of concession. However a contract of management must be celebrated, defining goals and tariff policies for the operator. In the concession, a municipal concessionaire or public–private partnership with municipalities and other private operators is established under a long term contract, usually from 30 to 50 years. The participation of private capital is allowed mainly in the delegation and concession models, and eventually in the direct management in case of partnership with State or municipalities (Marques and Berg, 2011; Pérez et al., 2019; ERSAR, 2021a).

According to the annual report issued by ERSAR in 2021 (ERSAR, 2021a,b), in Portugal, there are ten companies operating in the wholesale water supply market. Those companies and their identification codes used in the study are: Águas de Santo André (A1), Águas do Algarve (A2), Águas do Douro e Paiva (A3), Águas do Centro Litoral (A4), Águas do Norte (A5), Águas do Vale do Tejo (A6), Águas do Vouga (A7), Águas Públicas do Alentejo (A8), EPAL (A9) and ICOVI (A10). The wholesale companies are predominantly managed by concession (seven companies). The other three wholesale companies are managed by delegation. The retail water sector includes 233 companies, and most of them are managed directly by municipalities.

The indicator system used by ERSAR for benchmarking practices is detailed in Technical Guide 22 (ERSAR and LNEC, 2021). The volume of information annually acquired from the operators is vast, comprising water, wastewater and solid waste services. In the case of water supply companies, the performance indicator system of ERSAR presents 14 main metrics, grouped in three different dimensions: i) *Adequacy of the Interaction with the User*, ii) *Service Management Sustainability* and iii) *Environmental Sustainability*.

The ERSAR indicators directly related to asset management are included in the subgroup *Infrastructure Sustainability*, in the dimension of *Service Management Sustainability*. The other

subgroups in this dimension are *Economic Sustainability* and *Physical Productivity of Human Resources*. The *Infrastructure Sustainability* subgroup contains two main indicators: *pipeline rehabilitation* (%/year) and *occurrence of pipeline failures* (number of failures/100 km/year).

The dimension Environmental Sustainability in subgroup Efficiency of Utilisation of Environmental Resources includes also two indicators that are related to asset management and its effect on the use of resources: *actual water losses* (m^3 /year) and *energy efficiency of pumping stations* ($kWh/(m^3 \cdot 100m)$).

Additional metrics regarding asset management status are also collected by ERSAR, including the Infrastructure Knowledge Index, the Infrastructure Asset Management Index, the Infrastructure Current Value and the Infrastructure Replacement Cost. All this information has been informed annually by wholesale and retail companies.

The Portuguese water sector has been explored by several works that employed benchmarking techniques using DEA, such as Marques (2006), De Witte and Marques (2010a) and Henriques et al. (2022). ERSAR's indicators in a BoD composite-indicator approach are utilised by Henriques et al. (2020) to identify best practices and foster continuous improvement in wastewater operators. Mergoni et al. (2022) employs also ERSAR's indicators in a BoD approach to evaluate the environmental performance of Portuguese utilities. The quality of water supply service is evaluated by Pinto et al. (2017a,c) using ERSAR's metrics. Those benchmarking studies take advantage of using indicators developed under the procedures of ERSAR system, such as submission of data, validation and processing of results (Pinto et al., 2017a). None of these studies applied ERSAR metrics to assess the performance of water companies with a focus in asset management, which reinforces the innovative nature of this research.

In terms of asset management performance, the water systems in Portugal present quite heterogeneous results. In a survey conducted by the *Specialised Commission for Asset Management* from the *Portuguese Association for Water Distribution and Drainage* (APDA - *Associação Portuguesa de Distribuição e Drenagem de Águas*) in 2019, the results, including both retail and wholesale companies, show that in 54% of the companies do not follow asset management practices. From the companies that claim to have an asset management system, 41% do not set objectives for asset management and 57% work on asset issues using staff that is not dedicated only to that task. Only 4% of the water supply companies present a certification in ISO 55001. A considerable number of companies do not undertake asset condition analysis, and when they do, visual inspections prevail. Many businesses still do not do preventative maintenance. There is a significant reliance on paper and spreadsheet-based records. These results are worse in retail companies compared to bulk systems (APDA, 2019). Based on such findings, there is a significant space for enhancement.

6.4 Methodology

The methodology we propose consists of three steps. The first one consists of identifying the metrics that should be considered in the construction of the composite indicators (CIs). The second one deals with the development of a deterministic approach to compute the CIs. Finally, the third

step describes the calculation and evaluation of the robust and conditional CIs, accounting for contextual factors.

6.4.1 Construction of composite indicators (CIs)

This subsection presents the method of selecting the measures used for building the CIs in this study. For the construction of the CIs, we selected metrics among the data collected by ERSAR that reflect asset management practices in two distinct perspectives. Those metrics are aggregated to generate two different composite indicators.

Luís and Almeida (2021) explain that the practical results of adopting an asset management philosophy do not become apparent immediately after the start of asset management development programs in organisations. These programs typically require several years to effectively implement an asset management culture before the full material benefits become visible. As a result, managerial practices may be implemented, but the tangible results may not instantly reflect their impact on company performance. This fact supports the approach adopted in this study to develop one indicator that indicates tangible operational achievements (*Resource and Infrastructure Sustainability Index - RISI*) and another that represents the maturity stage in management systems (*Asset Management Maturity Index - AMMI*).

6.4.1.1 The Resource and Infrastructure Sustainability Index - RISI

The first CI is related to the companies' performance for the activities that aim to keep their infrastructures at suitable and sustainable operational levels. In that sense, the companies' tangible results in asset management can be expressed by this indicator. We named this indicator as *Resource and Infrastructure Sustainability Index (RISI)*. The RISI is made up of the following ERSAR metrics: pipeline rehabilitation (AA09a), occurrence of pipeline failures (AA10a), actual water losses (AA12a) and energy efficiency in pumping stations (AA13a).

The choice of these metrics has been driven by the available data collected by ERSAR and supported by previous studies, as those metrics are considered critical to monitor the performance of assets in water systems. The rate of pipeline rehabilitation and failures in water mains in Portugal and the importance of monitoring those indicators is discussed by Marques and Monteiro (2001), Ferreira and Carriço (2019), Cabral et al. (2019) and Santos et al. (2022). The use of water losses as one key indicator for the sector is detailed by Marques and Monteiro (2001, 2003) and Machado et al. (2009). Moreover, Loureiro et al. (2020) studied the energy efficiencies in water systems and concluded that inefficiencies are more related to the conditions of infrastructure and network layouts than to pumping issues.

All those metrics are included in the set of the aforementioned 14 main indicators required by ERSAR's system. Pipeline rehabilitation (AA09a) and occurrence of pipeline failures (AA10a) are included in the dimension *Infrastructure Sustainability*, and are directly related to assets' performance. The other two metrics, actual water losses (AA12a) and energy efficiency in pumping

stations (AA13a), are included in the dimension *Efficiency in the utilisation of environmental resources*, but they reflect the impact of assets' performance on the use of the available resources.

According to the Technical Guide 22 issued by ERSAR (ERSAR and LNEC, 2021), the pipeline rehabilitation metric (AA09a) is defined as the annual average percentage of supply and distribution pipelines older than ten years that were rehabilitated in the last five years. This metric is designed to assess the level of sustainability of service management, reflecting a continuous practice of pipeline repair to ensure their progressive renewal and appropriate average age of the network. The occurrence of pipeline failure (AA10a) is calculated as the number of pipeline faults per hundred kilometres. The actual water losses (AA12a) is the average daily volume of losses per unit of pipeline length in a year, expressed in cubic meters per pipeline kilometres in a day ($m^3/km.day$). This metric reflects the level of sustainability in the water supply service when utilising water as an environmental resource. Berg and Marques (2011) explain that the water-loss variable can be used as a proxy for inadequate maintenance costs, and recommend that it is modelled as an undesirable output. Finally, the energy efficiency in water pumping stations (AA13a) is defined as the normalised average energy usage for water pumping, indicating the sustainability of the assets in terms of using energy. It is expressed in kilowatt-hours by cubic meters per hundred meters of elevation.

Three of the metrics employed to compose RISI are undesirable, meaning that lower values are expected to denote better performance: AA10a, AA12a and AA13a. Only the metric AA09a that measures the pipeline rehabilitation is desirable, meaning that higher values indicate that the performance is better.

6.4.1.2 The Asset Management Maturity Index - AMMI

The second CI designed from ERSAR metrics expresses the focus of the companies in managerial practices regarding their physical assets. ERSAR highlights the importance of those aspects and requests water operators information about the knowledge of the their assets (*Infrastructure knowledge index - PAA31a*) and the features of the management systems they have implemented (*Infrastructure asset management index - PAA32a*). Those two facets of the companies' managerial practices represent crucial aspects of water systems' management. They used to be expressed by only one metric in the earlier versions of ERSAR's indicator system. However, ERSAR decided to specify these two indicators to obtain more detailed information, such as data about non-buried assets and a greater focus on data records in geographical information systems rather than on paper (ERSAR and LNEC, 2017). We propose to integrate the two indicators in the form of the *Asset Management Maturity Index (AMMI)*.

The *Infrastructure knowledge index (PAA31a)* aims to assess the company's knowledge about the infrastructure of the water supply service in its area of intervention (ERSAR and LNEC, 2021). The accuracy of asset information is crucial for successful asset management, and it depends on the quality of the data stored and the way the information is managed. The selection and specification of the data to be collected, and the quality of the strategic information systems where the information is stored and made available to users, are essential aspects of asset information

management. Furthermore, the effectiveness of linking the various information systems is also important, so that data from different information systems can be cross-referenced.

It is essential to evaluate the data quality regarding its accuracy, the scale used, consistency and reliability as well as ensuring a proper geo-referencing of data to manage infrastructures. In addition, data storage must be reliable, and the flow of information must be ensured at all stages of the data system processes, including acquisition, evaluation, recording, updating, archiving and use. All those aspects are reflected in the *Infrastructure knowledge index* (ERSAR and LNEC, 2017).

The *Infrastructure knowledge index* is calculated by adding the scores taken from the company's answers to a questionnaire. The total score results from the sum of the question scores and may vary between 0 and 200. The questionnaire is divided into classes covering different topics, as follows:

- (a) class A - Existence of infrastructure engineering drawings and layout,
- (b) class B - Information recorded on pipelines and connection branches,
- (c) class C - Information recorded on other infrastructure,
- (d) class D - Information recorded on measuring equipment,
- (e) class E - Information recorded on the state of conservation of infrastructures,
- (f) class F - Information recorded on interventions in the public network,
- (g) class G - Interconnection between the Geographic Information and other company's information systems and recording of risk factors.

According to ERSAR and LNEC (2021), the *Infrastructure asset management index (PAA32a)* is also determined by adding the score attributed to a set of questions related to the assessment of the company's asset management system concerning:

- (a) general asset management framework,
- (b) documentation and communication,
- (c) strategic planning
- (d) tactical planning
- (e) operational planning

This index may vary between 0 and 200. ERSAR takes advantage of the existence of international asset management reference standards, ISO 55000 and ISO 55001 (ISO, 2014a,b), and includes many of the principles and requirements present in the standard into the organisational aspects indicated in the *Infrastructure asset management index* (ERSAR and LNEC, 2017). Therefore, following ISO 55001, the companies are encouraged to deal with relevant internal and external features, major stakeholders, appropriate planning, leadership and commitment, responsibility

and authority definitions, proper procedures and documentation, process controls, continuous improvement actions and other managerial aspects.

Both the *Infrastructure knowledge index - PAA31a* and the *Infrastructure asset management index - PAA32a* are only provided in their aggregate form, with no information about the partial scores that give rise to them. If detailed information about these partial scores were available, the composite indicator might be constructed including the specific scores of each question.

6.4.2 Deterministic approach for CI calculation

In this subsection, we describe the first approach applied to the calculation of the composite indicators which is the standard deterministic CI. The CI is computed from BoD linear programming models. BoD models are DEA models that handle multiple outputs, corresponding to several metrics to be aggregated, and a dummy input with a unitary value for all DMUs. The outputs, in this case, are the selected metrics collected from ERSAR. We employed the BoD model based on a Directional Distance Function (DDF), as formulated by Zanella et al. (2015). This model can deal with desirable and undesirable outputs, without needing to adjust the scales of measurement. The weights formulation of the Directional Distance Function BoD CI model is presented in (6.1).

$$\begin{aligned}
 &\text{minimise} \quad \beta_{j_0} = - \sum_{r=1}^s y_{rj_0} u_r + \sum_{k=1}^l b_{kj_0} p_k + v \\
 &\text{subject to} \quad \sum_{r=1}^s g_y u_r + \sum_{k=1}^l g_b p_k = 1 \\
 &\quad \quad \quad - \sum_{r=1}^s y_{rj} u_r + \sum_{k=1}^l b_{kj} p_k + v \geq 0 \quad j = 1, \dots, n \\
 &\quad \quad \quad u_r \geq 0, \quad r = 1, \dots, s \\
 &\quad \quad \quad p_k \geq 0, \quad k = 1, \dots, l \\
 &\quad \quad \quad v \in \mathbb{R}
 \end{aligned} \tag{6.1}$$

In formulation (6.1), y_{rj} and b_{kj} are, respectively, the desirable and undesirable indicators for DMUs j ($j = 1, \dots, n$) and the values of y_{rj_0} and b_{kj_0} represent the indicators of the DMU j_0 under assessment. The index r stands for the set of desirable outputs ($r = 1, \dots, s$) and the index k stands for the set of undesirable outputs ($k = 1, \dots, l$). The model's decision variables are the weights, where v is associated with the dummy input, u_r is associated to the desirable outcomes r , and p_k with the undesirable outcomes k . The total number of DMUs is n , the total number of desirable outputs is s and the total number of undesirable outputs is l .

The directional distance vector is specified as $(g_y, -g_b)$, indicating the direction of expansion of desired outputs and contraction of undesired ones. The decision about the direction vector

used in the models is critical since it can influence the computed scores. Several solutions have been presented in the literature depending on the study's objective. Fried et al. (2008) address different options for applying direction vectors to guide the improvement of inputs and outputs in DEA models. Those authors discuss suggestions for the vectors' selection and advocate that this decision should be made according to the research purpose. Rogge et al. (2017) also explores alternatives for the vector to set the directions of improvement for desirable and undesirable outputs in BoD models. In this work, following Zanella et al. (2015) and Rogge et al. (2017) we choose the values of $(g_y, -g_b)$ as being equal to $(y_{rj_0}, -b_{kj_0})$. In this case, each DMU can improve by following the path indicated by its specific output metrics, allowing for a proportional interpretation of the resulting composite indicator value.

The factor β_{j_0} in (6.1) expresses the inefficiency level of DMU j_0 , representing the maximum expansion of desirable outputs and contraction of undesirable outputs that is feasible to satisfy the model's restrictions. The minimum feasible level of β_{j_0} is determined by optimisation, such that the DMU j_0 under assessment can select the weights that show it in the best possible light. The value of CI associated with j_0 , can be obtained as $1/(1 + \beta_{j_0})$. Consequently, the CI score ranges from 0 to 1, where 1 represents the best performance level. The deterministic CI is referred in this work as CI_{j_0} . If $CI_{j_0} < 1$, there is a linear combination of other DMUs that dominates in terms of overall performance. If $CI_{j_0} = 1$, the DMU j_0 is located in the best-practice frontier, meaning that it is not outperformed by any of the others DMUs included in the assessment.

Weight restrictions must also be included in the model to prevent assessments that could disregard certain indicators by assigning them weights equal to zero. A more detailed discussion about the several kinds of weight restrictions for DEA models is available in Wong and Beasley (1990), Allen et al. (1997) and Sarrico and Dyson (2004), among others. Zanella et al. (2015) proposes a formulation for AR-I restrictions in BoD models, using virtual weights restricted in terms of the proportional importance of the variables. These restrictions consider a hypothetical DMU whose outputs are equal to the average of all values observed in the DMUs in the sample, represented by (\bar{y}_r, \bar{b}_k) . The virtual weights of the "average DMU" are then constrained by percentage-based restrictions. The use of those AR-I restrictions presents the advantage of being identical for all DMUs, and according to Zanella et al. (2015), they represent the best choice to construct composite indicators and ranks. The AR-I restrictions are the most used weight restrictions in BoD models. In this study, only lower bounds expressed as percentages are used (ϕ_r and ϕ_k , respectively for desirable and undesirable indicators). Following Zanella et al. (2015), the weight restrictions are added to the BoD model and formulated as shown in (6.2). By avoiding zero weights, all indicators are given some degree of importance when computing the composite indicators.

AR-I weight restrictions

$$\begin{aligned} \frac{u_r \bar{y}_r}{\sum_{r=1}^s u_r \bar{y}_r + \sum_{k=1}^l p_k \bar{b}_k} &\geq \phi_r, \quad r = 1, \dots, s \\ \frac{p_k \bar{b}_k}{\sum_{r=1}^s u_r \bar{y}_r + \sum_{k=1}^l p_k \bar{b}_k} &\geq \phi_k, \quad k = 1, \dots, l \end{aligned} \quad (6.2)$$

A detailed explanation of the BoD model formulation and the use of weight restrictions AR-I is available in Zanella et al. (2015), D’Inverno and De Witte (2020) and Van Puyenbroeck et al. (2021).

In case there are no undesirable indicators among the components to be aggregated in the CI, the BoD model and the AR-I weight restrictions can be simplified as shown in (6.3).

$$\begin{aligned} \text{minimise} \quad & \beta_{j_0} = - \sum_{r=1}^s y_{rj_0} u_r + v \\ \text{subject to} \quad & \sum_{r=1}^s g_y u_r = 1 \\ & - \sum_{r=1}^s y_{rj_0} u_r + v \geq 0 \quad j = 1, \dots, n \\ & u_r \geq 0, \quad r = 1, \dots, s \\ & v \in \mathbb{R} \end{aligned} \quad (6.3)$$

AR-I weight restrictions

$$\frac{u_r \bar{y}_r}{\sum_{r=1}^s u_r \bar{y}_r} \geq \phi_r, \quad r = 1, \dots, s$$

6.4.3 Robust and conditional approaches for CI calculation

This subsection describes the generation of CIs following the robust and conditional approaches.

Some limitations on the use of the deterministic CI have been discussed in the literature, namely its great sensitivity to outliers in the sample and the difficulty in performing statistical inference. These limitations can be overcome by the use of the robust CI approach. The conditional approach allows accounting for the effect of exogenous contextual variables in a single stage when constructing CIs. Since its initial conceptualisation by Cazals et al. (2002) and Daraio and Simar (2005, 2007a), these techniques have been applied, revised and enhanced by an extensive number of studies: De Witte and Kortelainen (2013); Rogge et al. (2017); De Witte and Schiltz

(2018); Lavigne et al. (2019); D’Inverno and De Witte (2020); Fusco et al. (2020); Mergoni et al. (2022), among others.

In line with this stream of the literature, the computation of the robust CI is performed by drawing (for a very large number of times) at random with replacement units from the original set of DMUs and computing the CI estimates for each sample through the resolution of the BoD model. If a sample of size m is considered, the resulting CI will reflect the comparison with the best-practice frontier composed only by DMUs included in the sample of size m . If this sampling and calculation process is performed B times, where B is typically a high number, the effect of the outliers on the average efficiencies will be lessened since they will not appear in all the collected samples. The resulting robust CI, referred as $CI_{j_0}^m$ in this study, is the average of the CIs generated for all B samples of size m , as shown in (6.4), where $CI_{j_0}^{b,m}$ is the CI of DMU j_0 calculated using sample b .

$$CI_{j_0}^m = \frac{1}{B} \sum_{b=1}^B CI_{j_0}^{b,m} \quad (6.4)$$

When the results are calculated, it may happen that, for a given sample, the DMU under assessment (j_0) is not included in that sample, such that it may be more efficient than all the DMUs in the sample. In this case, the DMUs would be classified as “super-performing” and its score, $\beta_{j_0}^{b,m}$, would have a negative value. The more negative $\beta_{j_0}^{b,m}$ is, the higher the performance of the DMU, so $CI_{j_0}^{b,m}$ should increase as $\beta_{j_0}^{b,m}$ decreases. However, this can not happen if $CI_{j_0}^{b,m}$ is calculated as $1/(1 + \beta_{j_0})$. A solution to this problem is suggested by Mergoni et al. (2022) by modifying the calculation of $CI_{j_0}^{b,m}$ to adapt for the case of negative values of $\beta_{j_0}^{b,m}$ as detailed in (6.5).

$$CI_{j_0}^{b,m} = \begin{cases} \frac{1}{1 + \beta_{j_0}^{b,m}}, & \text{if } \beta_{j_0}^{b,m} \geq 0; \\ \log_{10}(1 - \beta_{j_0}^{b,m}) + 1, & \text{if } \beta_{j_0}^{b,m} < 0 \end{cases} \quad (6.5)$$

Figure 6.1 displays both functions applied to calculate $CI_{j_0}^{b,m}$. The original formulation (in blue), besides of being discontinued in $\beta_{j_0}^{b,m} = -1$, yields negative values for $CI_{j_0}^{b,m}$ if $\beta_{j_0}^{b,m} < -1$. This curve does not reflect the proportional increments in performance expected for the CI when the units are “super-performing”. On the other hand, the proposed formulation when $\beta_{j_0}^{b,m} < 0$ (in red) follows a similar trend as the original formulation for positive values of $\beta_{j_0}^{b,m}$ allowing the value of $CI_{j_0}^{b,m}$ to increase as the performance of the DMUs improves. Therefore, following Mergoni et al. (2022), the robust CIs proposed in this study are computed using the expressions in (6.5). This applies also for the computation of the robust conditional CIs as presented hereinafter.

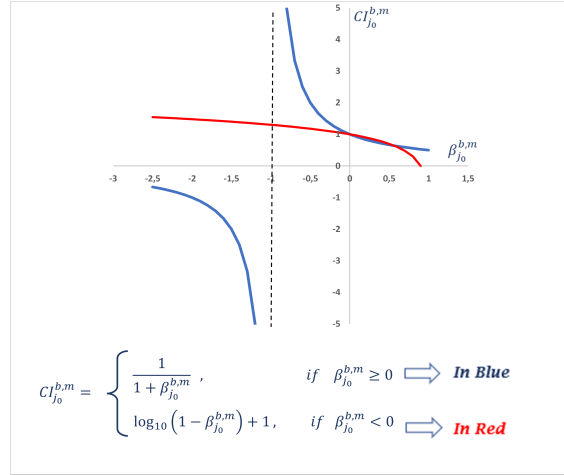


Figure 6.1: Comparison between the expressions used to calculate CI.

In order to account for the influence of the contextual variables, the robust conditional approach or, simply conditional approach, needs to be employed. This strategy is used to adjust the CIs to allow fairer comparisons by forcing the DMUs assessment to be performed with more similar DMUs according to exogenous characteristics. The procedure is analogous to the robust CI strategy, using B samples of size m and computing the CI as the average of all samples. The difference between this strategy and the robust approach is that instead of performing random sampling from a uniform distribution, the sampling is conducted using a similarity function. The similarity is measured using a kernel function estimated using the contextual variables. There are currently computing models to deal with both continuous and categorical context or exogenous variables (Li and Racine, 2003). The conditional CI, referred to as $CI_{j_0}^{m,z}$, is computed as the average of the conditional $CI_{j_0}^{b,m,z}$ for B samples as shown in (6.6).

$$CI_{j_0}^{m,z} = \frac{1}{B} \sum_{b=1}^B CI_{j_0}^{b,m,z} \quad (6.6)$$

After computing $CI_{j_0}^{m,z}$, the significance and the direction of influence of the contextual variables can be evaluated. The score ratio between the robust CI and the robust conditional CI ($CI_{j_0}^m / CI_{j_0}^{m,z}$) is non-parametrically regressed against the exogenous variables. Partial plots showing the variables' confidence intervals for different levels of the exogenous variables can be generated, and non-overlap intervals indicate that the effect of the context is significant.

If the ratio is decreasing as the environmental variable increases (that is, the regression plot displays a negative slope), it means that the conditional score is larger than the unconditional one just because compared among units more similar in terms of the contextual variables. In that sense, the environment plays an unfavourable role when it comes to the performance evaluation. On the contrary, if the regression plot displays a positive slope, the environment plays a favourable role. For a more detailed explanation, see Rogge et al. (2017); D'Inverno et al. (2021). For an analogous approach using DEA efficiency scores, see Walker et al. (2019).

6.5 Case study

This section details the case study analysed by the research. In subsection 6.5.1, the primary data set containing the metrics collected by ERSAR that form the composite indicators is presented. Subsection 6.5.2 displays the variables utilised to characterise the environment in which the companies operate.

6.5.1 Data collected

The study employs the metrics collected by ERSAR during five years, from 2016 to 2020¹, to construct the CIs RISI (Resource and Infrastructure Sustainability Index) and AMMI (Asset Management Maturity Index) as detailed in subsection 6.4.1 .

The methods developed for comparative performance, such as those based on DEA, provide better results if the number of DMUs is large. Thanassoulis (2000a) explains that one way to increase the number of DMUs is to treat each unit as a separate comparative entity in distinct units of time, through the use of a panel data. By doing that, the basic assumption to consider is that the technology remains stable over time to enable meaningful comparisons of performance. Given the observed time span and the nature of the water industry, this assumption is verified. The infrastructure cannot be changed rapidly as the investments in assets are primarily underground and deemed to last several decades. In that sense, the DMUs in this study are formed by the combination of company and year. For example, DMU A1-2016 means that the data of company *Águas de Santo André (A1)* for 2016 is being assessed. By choosing this strategy, the companies can be compared not only with other companies but also with themselves in different years, allowing the evaluation of their performance over time. Since *Águas do Douro e Paiva (A3)* was created in 2017, only four years of data are available for this company. Therefore the number of DMUs employed in the study is 49 instead the expected number of 50, considering that there are ten companies for five years of evaluation.

An examination in the data set indicates that two data instances are missing: the values for the metric AA13a for DMUs A5-2016 and A8-2020. The procedure recommended by Kuosmanen et al. (2002), Morais and Camanho (2011) and Henriques et al. (2020) for treatment of missing data in DEA was used in this case. Since the metric is undesirable, a large value corresponding to the maximum value of metric AA13a in the sample was assigned to both DMUs. This implies that the absence of data cannot favour the DMU in the performance assessment.

The descriptive statistics for the data related to the metrics that compose both CIs are presented in Tables 6.1 and 6.2.

¹ERSAR reports are available online in <https://www.ersar.pt/pt/site-publicacoes/Paginas/edicoes-anuais-do-RASARP.aspx>.

Table 6.1: Metrics that compose RISI.

ERSAR Code	Metric description	Metric definition	No. Obs.	Mean	St. Dev.	Min.	Max.
AA09a	Pipeline Rehabilitation (%/year)	Average annual percentage of pipelines with life higher than ten years rehabilitated in the last five years.	49	0.19	0.31	0	1.3
AA10a	Occurrence of Pipeline Failure (n^o / 100 km.year)	Number of failures in pipelines per 100 km in a year.	49	7.92	8.78	1	40
AA12a	Actual water losses (m^3 / km.day)	Actual water losses due to leakages and overflows per unit of pipeline length.	49	6.46	8.13	0.1	31.4
AA13a	Energy efficiency in pumping stations (kWh/m^3 .100m)	Average normalised energy consumption of pumping stations.	49	0.47	0.12	0.36	0.73

Table 6.2: Metrics that compose AMMI.

ERSAR Code	Metric description	Metric definition	No. Obs.	Mean	St. Dev.	Min.	Max.
PAA31a	Infrastructure Knowledge Index (Score 0-200)	Score of evaluation of the knowledge of the several infrastructures in different classes ranging from 0 to 200.	49	170.37	20.08	111	197
PAA32a	Infrastructure Asset Management Index (Score 0-200)	Score of evaluation in a questionnaire about asset management practices ranging from 0 to 200.	49	109.06	83.9	0	200

The correlation among the various metrics employed to build the CIs was investigated. The estimated Pearson correlation coefficients do not reflect a significant association between the pairs of metrics used in each CI, as the resulting absolute values of the coefficients are not close to one, as shown in Table 6.3. In this scenario, the low correlation supports incorporating all variables into the models.

Table 6.3: Pearson correlation coefficients - RISI and AMMI metrics.

CI	Pair of Metrics	Pearson Correl. Coefficient
RISI	AA09a-AA10a	0.334
	AA09a-AA12a	0.047
	AA09a-AA13a	0.362
	AA10a-AA12a	-0.210
	AA10a-AA13a	0.253
	AA12a-AA13a	-0.284
AMMI	PAA31a-PAA32a	0.357

6.5.2 Exogenous contextual variables

Four characteristics covering various contexts in which the organisations operate were chosen to analyse the influence of the background on their performance. The four factors are expressed also by variables collected and publicised by ERSAR on the annual report. Two of those variables, the management system and the typology of intervention area are categorical, and the other two, the volume of activity and the pipeline network length are continuous.

Variable PAA02a identifies the company's management system, and reflects the market structure of the water sector in Portugal. The companies *Águas Públicas do Alentejo* (A8), *EPAL* (A9) and *ICOVI* (A10), are operated by delegation, whereas all the other wholesale companies are operated by concession. This status remains for the whole period from 2016 to 2020.

Variable PAA14a reflects the typology of intervention area, in which the companies are classified as operating in rural, urban, or semi-urban settings. This criterion is mostly determined by population density. The urban companies are *Águas do Douro e Paiva (A3)* and *EPAL (A9)*, the rural companies are *Águas de Santo André (A1)*, *Águas Públicas do Alentejo (A8)* and *ICOVI (A10)*. The remaining five companies operate in semi-urban environment. The companies' status also does not change during the assessment period.

Table 6.4 presents the statistics for categorical exogenous variables between 2016 and 2020.

Table 6.4: Categorical exogenous variables.

ERSAR Code	Description	Definition	Obs.	Number of companies and percentage per category
PAA02a	Management System	Concession or Delegation.	49	Concession - 7 (69.4%) Delegation- 3 (30.6%)
PAA14a	Typology of Intervention Area	Rural areas, semi-urban areas or urban areas.	49	Rural - 3 (30.6%) Semi-urban - 5 (51.0%) Urban - 2 (18.4%)

The two continuous exogenous factors are represented by variables PAA50a and dAA15a. Variable PAA50a indicates a company's volume of activity, meaning the total billed volume of water supplied by the company per year. Variable dAA15a expresses the pipeline network length of the company in kilometres.

According to Haider et al. (2014), water supply systems include vertical components and linear components. Examples of vertical components are treatment plants, pumping stations and storage tanks, and the linear components include the water mains and pipeline networks. The linear components are usually much more expensive representing from 60% to 80% of the total cost of the water system. Therefore, the variable dAA15a was chosen to reflect the amount of assets that the company manages. Both continuous exogenous variables included are proxies of the company's size, but they are not strongly correlated with each other. The Pearson correlation coefficient is 0.377 and the p-value is 0.008.

Table 6.5 displays the descriptive statistics of the continuous exogenous variables. The effects of problematic and small samples have been already discussed by Henriques et al. (2022). Following those authors, and in order to maintain consistency in the study, we choose to include the two continuous variables as discrete variables (a similar approach can be found also in D'Inverno et al. 2021). Therefore those variables are split in two classes: above and below the median.

Table 6.5: Continuous exogenous variables.

ERSAR Code	Description	Definition	Obs.	Mean	St. Dev.	Median	Min.	Max.
PAA50a	Volume of Activity	Volume of water supplied ($m^3/year$)	49	60,680,458	62,916,421	30,448,818	978,630	215,392,064
dAA15a	Pipeline network length	Total length of pipelines (km)	49	1009.0	1148.4	497	26.8	3578.8

6.6 Results and discussion

In this section, the study's results are presented and discussed in three stages. The first part discusses the results of the calculation of the deterministic CIs and robust non-conditional (or simply robust) CIs. The second stage presents the estimation of the robust conditional (or simply conditional) CIs and the findings regarding the effect of contextual conditions on asset management performance. The last part presents a visualisation tool conceived to enable the combined analysis of both AMMI and RISI.

6.6.1 Deterministic and robust composite indicators' results

This subsection presents the findings from the calculation of the deterministic and robust CIs.

The deterministic CIs calculation follows the procedure detailed in subsection 6.4.2. Since RISI presents undesirable outputs, they are computed through the resolution of BoD model 6.1. For the AMMI calculation, BoD model 6.3 is employed, where only desirable outputs are considered. For the weight restrictions shown in 6.2 and 6.3, the values of parameters ϕ_r and ϕ_k were set to be equal to 0.05. Different values of ϕ_r and ϕ_k from 0.02 to 0.10 were tested, and the results remained very stable. After running this sensitivity analysis, an intermediate value of 0.05 was chosen.

For the robust CIs calculation, a sensitivity analysis was performed to decide the value of bootstrapping sample size m . Daraio and Simar (2007a) explain that there are no fixed rules neither automatic procedures to select the value of m . This value is typically an integer number smaller than n . These authors recommend to perform a sensitivity analysis, choosing several levels of m and evaluating the number of super-performing units. This number should decrease as m increases. In small dimension samples, the choice of m as being equal to the number of DMUs is recommended by Henriques et al. (2022). Following those authors, we choose for both indicators to use $m = n = 49$. Furthermore, at this level there is already a substantial decrease on the number of super-performing units and on the average CI values. The number of bootstrapping replications is chosen as $B = 2000$. The results are obtained using packages *Rglpk* (Theussl and Hornik, 2019) and *lpSolve* (Berkelaar et al., 2023) in R program.

Table 6.6 shows the descriptive statistics for RISI results and Table 6.7 displays the similar information for AMMI results. Looking at the averages of both indicators, a significant room for improvement can be noticed. Note that lower average scores signal a larger degree of heterogeneity among firms, taking the best-observed practices of the sample in a five-year period as reference. The CIs for all DMUs are reported in Table C.1 in Appendix C.1.

Table 6.6: Descriptive statistics for RISI results in deterministic and robust unconditional approaches.

	Average	St. Dev.	Min	Q1	Median	Q3	Max
Deterministic RISI CI (CI_{j_0})	0.799	0.079	0.637	0.771	0.801	0.840	1.000
Robust Unconditional RISI CI ($CI_{j_0}^m$)	0.835	0.092	0.646	0.796	0.834	0.877	1.138

Table 6.7: Descriptive statistics for AMMI results in deterministic and robust unconditional approaches.

	Average	St. Dev.	Min	Q1	Median	Q3	Max
Deterministic AMMI CI (CI_{j_0})	0.861	0.111	0.602	0.762	0.866	0.979	1.000
Robust Unconditional AMMI CI ($CI_{j_0}^m$)	0.865	0.110	0.606	0.768	0.873	0.979	1.004

A close look at the results for AMMI reveals that half of the DMUs present a CI above 0.866 in the deterministic case and above 0.873 in the robust unconditional analysis. Overall, the CIs allows the identification of the poorly performing companies and the highly performing ones, to guide improvements of the former by looking at the good practices of the latter.

Both indicators suggest that there is potential room for improvement among the companies. As the BoD model assigns the weights to each metric in the most favourable way, the underperforming companies cannot complain about the fairness of the evaluation. The highest ratings given to the top performers may not always indicate that there is no potential for further improvement in absolute terms. It simply means that, based on the data available, these companies represent the best observed performance in the period under consideration. The evolution of productivity levels over time is captured by the movement of the best-practice frontier, whereas cross-sectional assessments of efficiency only evaluate the distance to the frontier at a given moment in time. This benchmarking exercise can be beneficial to the determination of policies both for the regulatory entity and the companies themselves.

6.6.2 Effect of exogenous contextual variables

This subsection presents the calculation of robust conditional CIs, which reveals companies' performance taking into account the operating context. Besides the use of R packages *Rglpk* (Theussl and Hornik, 2019) and *lpSolve* (Berkelaar et al., 2023), in this analysis the *np* package was employed in R software to perform sampling according to the similarity level of DMUs and also to execute the non parametric tests of significance (Hayfield and Racine, 2008). The *np* package focuses on kernel approaches that are suitable for the combination of continuous and categorical data.

As previously discussed, the continuous variables need to be converted to discrete ones in this analysis due to the small sample size. For the same reason, the effect of exogenous factors can not be addressed using one model combining all variables as discussed in Henriques et al. (2022). The computation of the conditional CIs and significance tests has to be performed individually for each exogenous variable in a first stage. In a second phase, only the significant variables are included in the final calculation to generate the conditional CIs. The potential for omitted variable bias in this case may be a concern, yet this method was deemed valid as the aim of the analysis was to pursue evidence of correlation, not necessarily causal relationships. The option to include one variable at a time furthers a practical approach that enables the identification of the contextual factors influencing the outcomes.

Figure 6.2 reports the results obtained for the Conditional BoD model considering the variable PAA02a (Management System). The confidence intervals shown in Figure 6.2 do not overlap, and the p-value of the hypothesis test used to compare the groups (Kernel regression significance test) is smaller than 2.22×10^{-16} in both cases, which means that the difference between concession and delegation management systems is significant regarding the performance measured by both indicators. The score ratio between robust and robust conditional CIs for the delegation management system in both indicators is higher, indicating that the delegation environment is more favourable for the performance in both perspectives of RISI and AMMI. We hypothesise that this fact is concerned with the more experience the delegation companies have already got in asset management practices. Historically, the emphasis on asset management began in Portugal with delegation-managed firms. Since 2006, EPAL, one of the largest delegation firms, has been the first wholesale water provider to focus on asset management procedures. It was also the first wholesale company in the country to acquire ISO 55001 certification (Luís and Almeida, 2021).

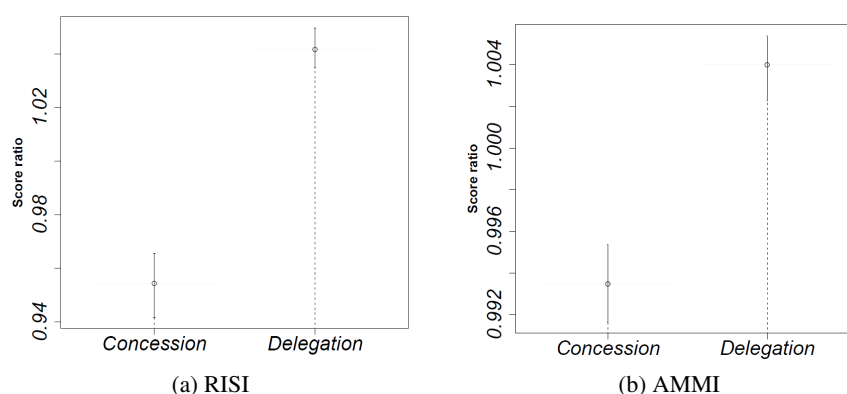


Figure 6.2: Effect of each exogenous variable - management system.

The ownership and management approaches of water systems have been extensively discussed in the literature, with controversial results. In the review conducted by Berg and Marques (2011), out of 47 studies focusing on that issue, 18 found that private water companies perform more efficiently than the public ones, 12 concluded that public water utilities are more efficient than the privates, and 17 reach inconclusive results. In general, the private sector tends to improve labour productivity but often increases capital expenses, and the opposite holds for the public sector. We highlight that those studies do not emphasise only asset management practices, but efficiency in general. Furthermore, in the management systems for the bulk companies in Portugal, the public control is more direct in the delegation system than in the concession.

The results for the conditional CI approach using variable PAA14a (Typology of Intervention Area) can be seen in Figure 6.3. The results for the kernel regression significance test in this case indicate that this contextual factor is also significant for the companies' performance in asset management. The p-values are less than 2.22×10^{-16} , both for RISI and AMMI.

In the case of RISI, rural environment is more favourable, achieving higher values in the score ratios between the robust and conditional CIs. A possible reason for that may be related to the fact

that the rural water networks are younger in Portugal, mainly due to the expansion in investments towards the rural areas in recent decades. Younger water assets have reduced chances of deterioration and leakage, which may explain why rural settings operate more efficiently. Rurality has been already studied as an exogenous factor in the context of global efficiency by Walker et al. (2019), that concluded that higher population densities in urban setting are more favourable to increase the efficiency due to scale economies.

The urban environment score ratio, on the other hand, is much higher than the other settings for the AMMI, suggesting that urban enterprises have superior asset management systems. This phenomenon might be connected to urban companies' knowledge of their assets. Since the *Infrastructure knowledge index*, required by ERSAR, is a component of AMMI, the information the companies retain about their assets affects the result of that indicator. In urban settings, the assets' inventories and records are more accurate, which may explain this finding.

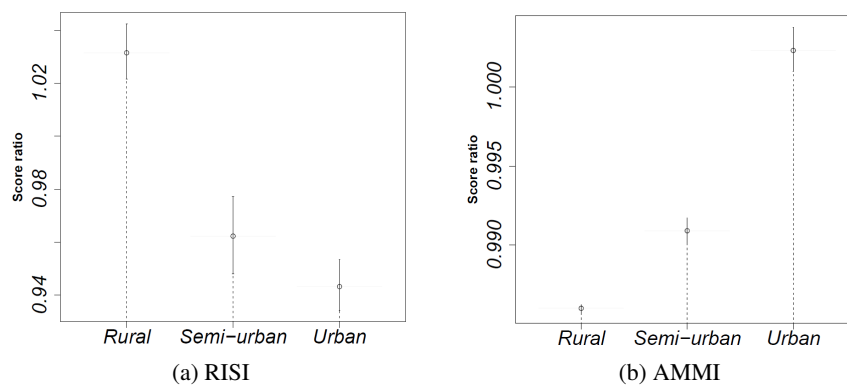


Figure 6.3: Effect of each exogenous variable - typology of intervention area.

The results obtained from the analysis of the conditional CIs employing the variable PAA50a (Volume of activity) are displayed in Figure 6.4. As previously stated, the level “High” in the graph includes the DMUs that present the volume of activity higher than the median of all DMUs, while the DMUs labeled “Low” have a lower volume of activity than the median. In this case, the differences between the groups were found to be non-significant for both indicators. The p-values are 0.399 for RISI and 0.231 for AMMI, revealing that the volume of activity expressed by the amount of water supplied by the wholesale companies does not affect their performance in asset management. Water systems are considered large by the European Commission, if they supply more than 1000 m^3 of water per day or serve more than 5000 people (European Commission, 1998). Looking at the data in Table 6.5, we can see that all the companies included in this analysis provide a larger volume of water than $1000 \text{ m}^3/\text{day}$, and at this scale no difference can be noticed among the analysed companies in asset management regarding the volume of activity.

Similar results are seen for variable dAA15a (Pipeline network length). The graphs in Figure 6.5 suggest that there are no significant differences regarding the two levels of pipeline network length considered in the analysis. As previously noted, the two categories are “Low” for less than the median of all DMUs and “High” for larger than the median.

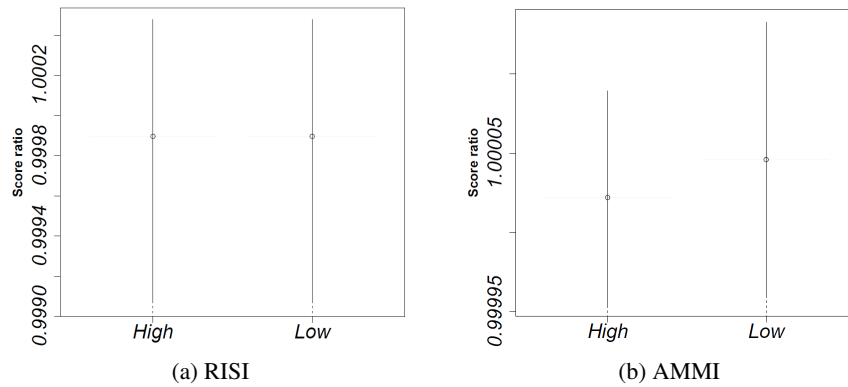


Figure 6.4: Effect of each exogenous variable - volume of activity.

After the effect of all variables is evaluated individually, the robust conditional CIs are computed utilising the two factors considered significant: *Management system* and *Typology of intervention area*. The resulting CIs are also shown in Table C.1 in Appendix C.1 and the descriptive statistics are displayed in Table 6.8.

In the conditional assessment, the companies are predominantly compared to more similar units. Also in this case, it is possible to identify potential room for improvement. Once more, the companies found poorly performing are granted the fairness of the assessment and cannot blame the evaluation system.

Table 6.8: Descriptive statistics for RISI and AMMI in robust conditional approach.

	Average	St. Dev.	Min	Q1	Median	Q3	Max
Robust Conditional RISI CI ($CI_{j_0}^{m,z}$)	0.891	0.088	0.667	0.829	0.913	0.953	1.057
Robust Conditional AMMI CI ($CI_{j_0}^{m,z}$)	0.906	0.084	0.615	0.865	0.898	0.998	1.000

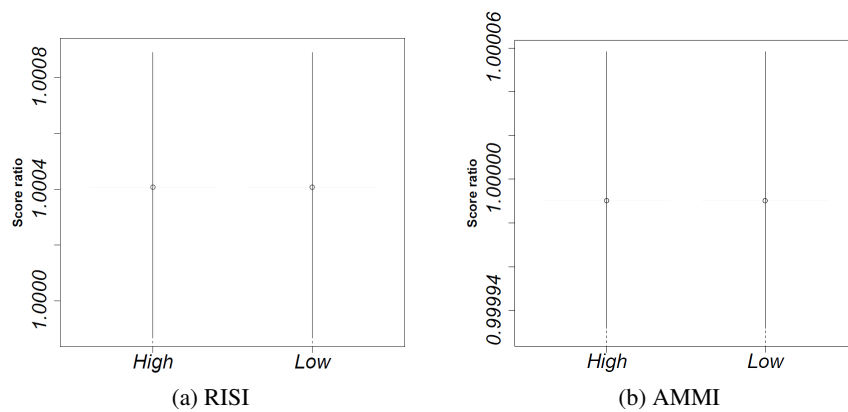


Figure 6.5: Effect of each exogenous variable - pipeline length

6.6.3 Visualisation framework for the combined analysis of asset management dimensions

A visualisation model inspired by the BCG (Boston Consulting Group) matrix (Hax and Majluf, 1983) was created to enable for the combined analysis of companies in both indicators (RISI and AMMI) in an integrated manner. In this framework, the companies under assessment are classified according to the value of the CIs compared to the median of the entire sample. Figure 6.6 distinguishes four categories to illustrate the companies' performance compared to peers, as follows:

- (a) Stars - when both RISI and AMMI are higher than their median values. In this case, the companies provide tangible results and demonstrate consistent asset management techniques, compared to peers.
- (b) Soldiers - when RISI is higher than median and AMMI is lower or equal than median. In this category, the companies take good care of the assets, meaning that the assets are maintained in suitable operational conditions compared to peers, but management strategies are not properly implemented.
- (c) Infants - In this class, both RISI and AMMI are lower or equal than the medians. The Infants give the first steps in the organisation for asset management and their operational performance is worse compared to peers.
- (d) Learners - The Learners present AMMI higher than the median and RISI lower or equal than the median. They have been working on robust management systems but their achievements in asset management are worse than most of their peers.

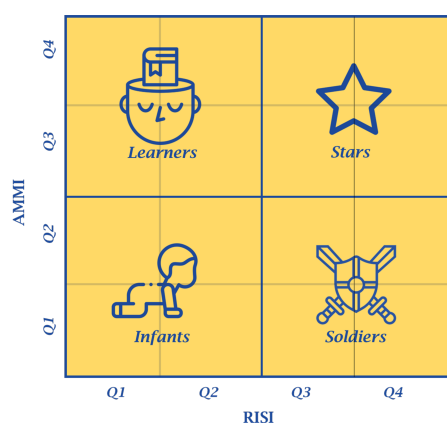


Figure 6.6: Visualisation model - RISI and AMMI.

The complete classification for all the companies is presented in Table C.1 in Appendix C.1.

Figure 6.7 displays the positions of the companies for the first and last years considered in the robust conditional assessment to highlight the changes in both CIs across time. When the data for

2016 and 2020 are compared, a tendency towards increasing both indicators can be noticed for most companies, suggesting an improvement in the sector's asset management practices.

Looking at the AMMI results, all the companies present better results for their management practices, between the first and the last years of evaluation. The same comparison for the RISI results reveals only two exceptions to this trend: the companies *Águas de Santo André* (A1) and *Águas do Vale do Tejo* (A6). *Águas de Santo André* (A1) displays significantly worse results for water losses (AA12a), which raised from $0.5 \text{ m}^3/\text{km.day}$ in 2016 to a range between 1.8 and $2.6 \text{ m}^3/\text{km.day}$ in the following years. The unfavourable trend is also repeated for the energy efficiency in pumping stations (AA13a) which was $0.49 \text{ kWh}/\text{m}^3.100\text{m}$ in 2016 and jumped to values superior to $0.62 \text{ kWh}/\text{m}^3.100\text{m}$ from 2017. This company is also disfavoured by the lack of investment in network rehabilitation, as metric AA09a is null for the whole period, and by the significant number of pipeline failures (AA10a), which are higher than the sector average for all years. As a result of this poor performance, *Águas de Santo André* dropped from the category Soldier to Infant in 2017, and remained in the same category since then. The case of *Águas do Vale do Tejo* (A6) is different since the worsening in RISI is minimal. This company presents relatively stable results over time, but when the metrics between 2016 and 2020 are compared, the number of failures in pipelines (AA10a) increased from 6 to 7 failures per 100km.year.

In all the other cases, improvements are noticed in both indicators. This information may be utilised as a motivator to continue with asset management practices in the future.

The use of combinations of company and year as units of assessment allow for the comparison of a firm's performance with itself across time. This procedure is known as internal benchmarking (see also Piran et al. (2021), for further details on this topic). The visualisation framework may be used to depict the progression of the companies' performance throughout the period under assessment. Figure 6.8 displays examples for three companies.

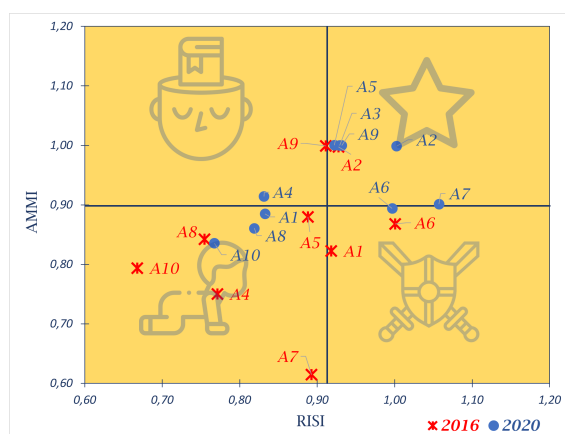


Figure 6.7: Visualisation model - Comparison between the first and the last year of assessment.

The progression of company *Águas do Algarve* (A2) is presented in Figure 6.8a. This organisation has consistently learned from implementing managerial approaches over the years. It started in 2016 already as a Star, and by keeping the performance in managerial features at a high

level, it keeps improving its operational results, remaining always in the same category. *Águas do Norte (A5)* has also been improving its management system compared to peers over the years, being certified in ISO 55001 in 2019. The tangible results have also been improving as shown in Figure 6.8b, even though an unsustainable major progress from 2016 to 2017 led to a decline in 2018. Since 2019, the company performs as a Star. The results of *Águas do Vouga (A7)* depicted in Figure 6.8c indicate that the company has also learned from the implementation of managerial approaches over the years. Its operational results have improved, and finally, in 2020, it performs as a Star.

By analysing each company's evolution individually through the 2x2 matrix, one can identify in which period the company adopted best practices and better understand what actions are required to support improvements. The fact that performance can be evaluated in two dimensions, using the joint visualisation of managerial elements (AMMI) and tangible results (RISI), may support the companies' overall internal analyses.

A first policy recommendation for a given company should be to analyse its evolution over time through an internal benchmarking process. If there is change between categories, or even if there is a variation in performance within the same category, the company can use the periods when its performance was superior and try to determine which factors led to that success. Next, the company should analyse the performance of its peers, especially those that are subject to the same context, and try to set targets based on the results of these peers that may help the company improve its performance.

6.7 Conclusion

Among the main findings of this work, a novel approach to benchmark wholesale water supply companies regarding asset management practices is developed using Benefit-of-the-Doubt (BoD) directional distance models to construct composite indicators (CI). The BoD models provide an innovative way of applying the metrics collected annually by the Portuguese regulatory authority, ERSAR. This strategy benefits from reliability of ERSAR's data and well-established procedures for monitoring companies and acquiring information. This study is the first to use these data to evaluate the success of organisations in terms of asset management methods, which fills an important gap in the literature.

In addition to the traditional deterministic strategy for generating CIs, robust and conditional approaches are used to allow statistical inference and examine the influence of contextual factors on firms' performance. The findings suggest that companies with a management system based on a delegation model show better asset management performance. Furthermore, a rural setting appears to be more favourable for achieving good operational results in assets, whereas better management systems are expected to benefit from urban environments.

The findings of this study enable water businesses to understand better where they stand in terms of asset management performance compared to other firms and themselves over time. These findings are highly relevant because they may help organisations make better decisions about

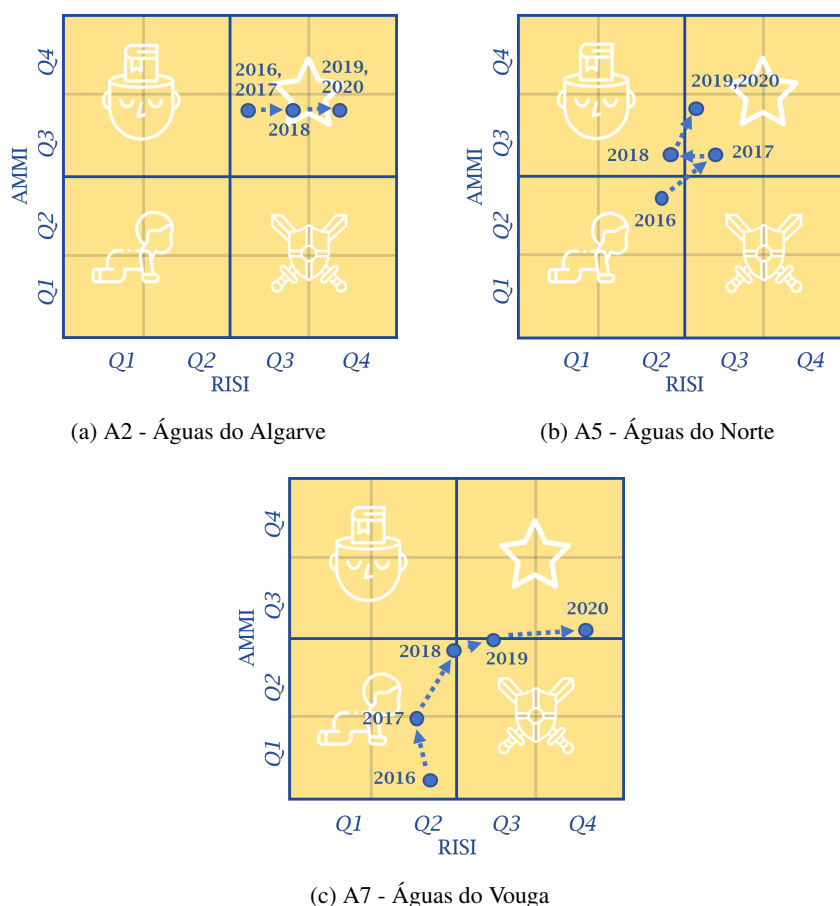


Figure 6.8: Examples of three companies' evolution from 2016 to 2020

where to focus on promoting continuous improvement efforts related to asset management techniques, which represent a vital issue in the water industry. Furthermore, the insights uncovered by this research may be used by the regulator to set policy targets for the water sector following the objectives of the sunshine regulation method and promoting the overall efficiency of the sector. A visualisation model for the combined evaluation of the two CIs is also presented, and examples of companies' evolution across the assessment period are discussed.

The presented study gathers in an innovative way a number of relevant aspects. First, it makes use of reliable and accurate data collected from the regulatory entity in the Portuguese water industry. Second, the BoD technique is suitable to reduce potential conflicts in the evaluation assessment, since companies cannot complain about the fairness of the aggregating scheme (being by design the most favourable one). Third, the conditional analysis favours the comparison of units under a more similar context, allowing for an even fairer analysis. Finally, the strategy combining internal and external benchmarking allows the assessment of a company over time and the visualisation model enables the combined evaluation of operational results and managerial enablers.

Some limitations of the study derive from the small sample size used. As a result, the contextual variables cannot be all included in a single model and the interaction between all variables cannot be investigated. The reduced sample size also prevents the use of continuous exogenous variables in their original form. The investigation can be extended to the 234 Portuguese retail companies in future developments. A larger sample size may allow a more detailed analysis of contextual factors. Furthermore, the envelopment formulation of BoD models may be used to determine the best peers and targets regarding asset management practices for this broader sample of companies.

The proposed tools and the overall analysis should encourage the companies and the regulator to collaborate for a richer collection of indicators associated with the assets and asset management practices. For example, in most of the cases, companies do not report relevant information such as the *Infrastructure Value Index*, the *Infrastructure Current Value* and the *Infrastructure Current Value*. A richer dataset can help the regulator and the companies better identify the best practices, enhance internal management, and design policies to foster a continuous improvement of asset management activities.

Guiding improvements in asset management through the identification of peers and targets in retail water companies

This chapter aims to present an evaluation of the performance of water supply utilities operating at the retail level in Portugal concerning asset management practices. The study's main innovative feature is identifying peers and targets to guide improvements in the sector. Reliable data collected by the regulatory authority for water and waste services in Portugal (ERSAR) are employed to design two composite indicators reflecting different dimensions of asset management: operational conditions and management systems. Based on the Data Envelopment Analysis technique, the Benefit-of-the-Doubt model is employed in robust and conditional formulations. The role of the context on utilities' performance is also investigated. The results show that the direct management model is unfavourable concerning developing structured management systems, whilst urban environments favour managerial advancement. Rural and semi-urban environments favour "good" operational results in infrastructures. The pool of peers obtained for each utility and the quantification of targets based on the observed achievements by those peers facilitates the search for industry best practices and promotes continuous improvement. Given the high heterogeneity in asset management performance within the sector, the utility-specific target-setting approach illustrated in this chapter can support a regulatory policy review for determining more realistic goals.

7.1 Introduction

Providing access to clean water is of utmost importance for the health and well-being of all individuals. Water is essential for human life and increasingly needed to produce energy, generate food, manufacture products, and provide services. According to the latest Global Water Security Report, the percentage of the world's population using safely managed drinking water increased from 70% to 74% between 2015 and 2020. However, this rate is insufficient to meet the target set by the United Nations Sustainable Development Goals of achieving universal access to water by 2030. Two billion people were still lacking access to water services in 2020 (United Nations, 2022). This problem is further exacerbated by climate change, which brings more frequent and severe droughts, floods, and increasing sea levels. Additional challenges include population growth,

urbanisation, and lack of infrastructure maintenance and management. Consequently, it is necessary for the water sector to become more resilient so that it can withstand shocks and stresses (Lombana Cordoba et al., 2022).

These challenges require that water infrastructures are maintained in reliable conditions. Unfortunately, the majority of water systems are in severe disrepair due to the short-term and narrow focus strategies used in the sector, which have resulted in the deferment of necessary investments. According to a recent report by EurEau - the European Federation of National Associations of Water Services representing 30 European countries, the rate of water loss in Europe was found to be 25.1% (EurEau, 2021). The report also revealed substantial discrepancies in the rates among member countries, with the Netherlands reporting the lowest rate at 5%, while Bulgaria had the highest rate at 61%. According to the American Association of Civil Engineers (ASCE, 2021a), water mains break every two minutes in the United States, resulting in the loss of 6 billion gallons of treated water daily. This volume is equivalent to filling more than 9,000 swimming pools, and equates to US\$ 7.6 billion lost in 2019.

Urban water infrastructures are capital-intensive, expensive, long-lasting, and exclusive assets, which cannot be shared by multiple service providers, and represent a significant portion of municipal public assets' value. Asset management, a modern expression for a centuries-old practice that focuses on managing infrastructure assets, has emerged as a more comprehensive and well-devised strategic approach over the past few decades (Amaral et al., 2017). It represents a potential solution to deal with water infrastructures, ensuring the economic health and welfare of modern communities (Alegre, 2010). Formalised since 2014 in a series of international standards, the ISO 55000 (ISO, 2014a), asset management involves an extensive system that requires organisations to balance cost, risk, performance and life cycle and extract the maximum value from their physical assets. Almeida et al. (2021) discuss that asset management techniques and principles allow an organisation to structure a governance model to achieve sustainable levels of service and performance. To ensure integration and successful implementation, asset management should be grounded in plan-do-check-act (PDCA) principles and divided into three levels of planning: strategic, tactical, and operational. At each level, defined objectives, assessment criteria and targets, diagnosis, action plan development, and implementation are key activities that should be undertaken for effective asset management (Alegre, 2010).

Benchmarking is a common practice in organisational management used to evaluate processes against best practices of peer entities in an industry or sector. When the best-in-class entities are identified, the managers are able to set targets that enable them to learn from others, measure their performance and guide improvements. This research is aimed at performing a benchmarking exercise with a set of Portuguese water utilities operating at the retail level, by focusing on their asset management practices.

Asset management applications were introduced in the Portuguese water sector in the beginning of century XXI, and even though some improvement effort has been carried out, the results are not uniform among all operators (Luís and Almeida, 2021). Different ownership and management structures coexist, resulting in significant heterogeneity in governance mechanisms and

asymmetrical access to funding that are necessary to cope with necessary investments. More than 200 utilities operate in the retail market and most of them are directly controlled by municipalities. Those service providers are responsible for the storage and distribution of treated water received upstream by larger-scale utilities operating the bulk market. The bulk or wholesale utilities extract, treat and distribute water to the retail market in Portugal.

In Portugal, the regulatory agency ERSAR (acronym in Portuguese for Water and Waste Services Regulation Authority) annually gathers a vast collection of metrics that are suitable for benchmarking purposes. Several of those metrics reflect asset management factors that can be employed to assess the performance of the retail water operators. These indicators are used as input data for this research.

The Benefit-of-the-Doubt (BoD) technique based on Data Envelopment Analysis (DEA) is applied to construct composite indicators, in order to measure the performance of the various utilities in two dimensions: assets' condition and managerial features. Additionally, the role of the context in which those utilities operate was also taken into consideration in the benchmarking study. Finally, suitable peers and targets for operators are determined.

The relevance of the study relies on the critical conditions presented by the Portuguese water sector in terms of asset management and the urgent needs to foster improvements in this area. The use of ERSAR metrics to perform benchmarking studies in the retail water market in Portugal has been explored by several studies (Marques, 2006; De Witte and Marques, 2010a; Henriques et al., 2022; Mergoni et al., 2022; Pinto et al., 2017a,c; Amaral et al., 2022, 2023). The study developed by Vilarinho et al. (2023c) focused exclusively on asset management practices, but covered only the bulk market. The development of a methodology to identify the most appropriate benchmark counterparts and targets for a set of water retailers concerning asset management practices has yet to be covered in the literature, representing the main contribution of this chapter.

The remainder of the chapter is divided into the following sections: section 7.2 provides a short literature review, section 7.3 explains the methodology, section 7.4 gives details about the case study, section 7.5 displays the results and discusses the findings, and, finally section 7.6 presents the conclusions.

7.2 Literature review

The literature review includes a discussion about benchmarking practices using DEA applications in retail water utilities (subsection 7.2.1), the characterisation of the Portuguese water sector (subsection 7.2.2), and a discussion of asset management features of the water sector in Portugal (subsection 7.2.3).

7.2.1 Benchmarking practices in retail water companies

Benchmarking is a common practice used to compare performance with standards, aiming to identify areas for improvement. Metric benchmarking employs indicators to measure an entity's performance over time and compare it to its peers. Entities can thereby evaluate how they measure up

against industry standards or observed practices of peers, track progress toward goals, explore best practices, and optimise operations and resource utilisation. Developing a reliable benchmarking method enables spotlighting the better and worse performing service providers, setting incentives on organisation performance and offering visibility on the processes and mechanisms that work and those that do not work (Mumssen et al., 2018).

Marques and De Witte (2010) detail the vital role of benchmarking practices in the performance the water sector. Regulators often evaluate the efficiency of utilities using a set of practices known as “yardstick competition” that is utilised when direct competition between public service providers is not possible. The main idea of yardstick competition is to compare the performance of service providers in the same sector creating an artificial competition between them. The key advantages of yardstick competition include incentives to boost information sharing and openness, as well as efficiency, innovation, and quality of service. As a result of yardstick competition, the knowledge acquired from other utilities is used to redirect the incentive of the utility under examination to enhance its efficiency. Yardstick competition is performed in the water sector using two approaches. The first one, known as price yardstick competition, employs benchmarking practices to set tariffs. The second approach to yardstick competitions is often softer and involves mandatory benchmarking mixed with open disclosure of performance data with no relation to price setting. This lighter mode of yardstick competition is known as sunshine regulation and has been implemented in many countries, such as Australia, Argentina, Holland, Denmark and Portugal. Sunshine regulation became popular in the water sector, and is sometimes employed as an initial step toward more demanding and tighter regulation processes (Marques, 2006).

In a benchmarking context, a systematic process can be helpful to estimate efficiencies and obtain by-products of the measurement exercise corresponding to targets for inputs and outputs and peers that serve as benchmarks for each utility. Data Envelopment Analysis (DEA) models can address these requirements. Among the techniques available, Marques (2006) championed using DEA as the most consensual and widespread approach for evaluating water systems. Non-parametric approaches, including DEA, differ from those using engineering standards or production functions with conceptually stipulated functional forms. DEA, established initially by Charnes et al. (1978), is a data-driven, non-parametric approach that evaluates performance compared to best practices identified across a group of units known as DMUs (Decision Making Units). The use of DEA identifies an efficient best-practice frontier, and inefficient units are rated based on their distance from that frontier. The calculations are performed using linear programming models to identify the optimal weights applied to inputs and outputs, from which the efficiency scores are obtained.

The selection of an appropriate reference set is of critical importance when conducting benchmarking activities. It requires organisations to identify a peer group in their sector or industry that presents proper performance measures from which to learn. DEA-based applications facilitate the establishment of best practices and benchmarks, as ultimately DEA analyses offer information on both target setting and peer identification. Methodologically, in DEA, for a particular DMU under assessment, only a section of the DEA efficiency frontier should be considered the common

best-practice frontier. This common best-practice frontier will be the facet of the DEA efficiency frontier spanned by a set of technically efficient DMUs, which can be seen as a common reference group. This reference set represents the DMU's peers. Targets will then result from projections of this DMU toward the common best-practice frontier. Selecting the peer set that provides the closest targets ensures the identification of the globally most similar best practices. Therefore, the DMU can identify the easiest way to improvement (Ruiz and Sirvent, 2016, 2022). Thanassoulis et al. (2008) explains that targets represent the levels of inputs and outputs that render a DMU efficient. These authors highlight that, by focusing on observed operating practices, DEA tends to be very useful in providing a starting point for setting performance targets. Simplified and interactive procedures incorporating user preferences have been applied to target identification. Their relevance lies on improving nontechnical users' comprehension of the evaluation process which supports the organisational learning (Pereira et al., 2021).

DEA applications can be used to aggregate several metrics in the form of a *composite indicator (CI)*, which is known as the "Benefit-of-the-Doubt" (BoD) approach. This strategy was proposed to evaluate macroeconomic performance by Melyn and Moesen (1991) and popularised by Cherchye et al. (2007). Zanella et al. (2015) explain that there are only output measures to be aggregated in a BoD, so all DMUs are assumed to be similar regarding the inputs. Thus, a unitary input is considered in the BoD as opposed to a standard DEA linear programming model that presents inputs and outputs. Being based on DEA, the BoD method is data-driven and avoids the need for consultation with stakeholders to determine the aggregation weights for the individual metrics. Additionally, since the weights generated as outcomes of a BoD model can handle the conversion of units, the metrics can be employed using their own units of measurement, avoiding the need for normalisation. BoD models are also used to identify peers (Lavigne et al., 2019; Zanella et al., 2013; Morais and Camanho, 2011) and targets (Wüst and Rogge, 2021; Pereira et al., 2021).

The efficiency of water and wastewater operators has been vastly explored in the literature with studies performed worldwide, including Australia (Byrnes et al., 2010), Brazil (Tourinho et al., 2022a,b), Canada (Wang et al., 2018), China (Dong et al., 2018), Italy (Romano and Guerrini, 2011; Lo Storto, 2018; D'Inverno et al., 2021), Japan (Marques et al., 2014), Palestina (Alsharif et al., 2008), Peru (Berg and Lin, 2008), United Kingdom (Walker et al., 2019; Thanassoulis, 2000a,b) among others. Several works using DEA have investigated the Portuguese water sector (Marques, 2006; De Witte and Marques, 2010a; Henriques et al., 2022; Mergoni et al., 2022; Amaral et al., 2022). Literature reviews covering benchmarking practices in water systems can be found in Berg and Marques (2011), that analysed 190 benchmarking studies using quantitative methods and Goh and See (2021), that reviewed 142 articles published between 2000 and 2019 on that subject.

The DEA approaches available in the literature include the computation of robust efficiency scores to minimise the effect of outliers and robust conditional efficient scores, that allow statistical inference and adjust the scores produced according to the environment. The robust and robust conditional approaches have been widely employed to evaluate water systems (e.g. De Witte and

Marques 2010a, Mbuvi et al. 2012, Marques et al. 2014, D’Inverno et al. 2021, Mergoni et al. 2022). The effect of the context is characterised by a separate set of data from variables that do not enter directly in the computation of the scores but are used to guide the sampling process of the DMUs under evaluation. Carvalho and Marques (2011), in their study of overall performance measurement in 66 Portuguese water utilities, explain that the influence of the operational environment on efficiency must be taken into account. The comparison between water utilities operating under highly diverse contexts should be avoided. Therefore studies that do not adjust the efficiency measurement to the context in which the utilities operate can lead to unrealistic scores.

In a fragmented and heterogeneous market that is typical from the retail water sector, benchmarking exercises based on DEA/BoD models present the ideal fit for sunshine regulation practices, given their capacity to consider the environment in which utilities operate, identify genuine reference peers, and suitable performance targets. Those features support the selection of those tools for this study. Another benefit that reduces the chance of complaints in case of undesirable results is the flexibility that DEA-based techniques offer to determine the most favourable weights for each DMU.

7.2.2 The water market in Portugal

The Portuguese water sector experienced a complete structural reconfiguration by implementing new public policies for water and waste services initiated in 1993. Since then, Portugal has suffered a substantial transformation in social well-being, with relevant impacts on the environment and public health. Baptista (2014a) describes that the public water systems served only 81% of the homes on Portugal’s mainland in 1993. Regarding water quality, just 50% of the population was supplied with safe water according to national and European legislation. The service currently covers 96% of residential units with a quality above 99% (ERSAR, 2021a,b). Despite the notable geographical discrepancies between urban and rural regions, as roughly 99% of urban residences have access to public water supply services, compared to less than 90% in rural areas, the water sector reforms in Portugal represent an outstanding achievement (Baptista, 2014a). Paul Reiter, former Executive Director of the International Water Association (IWA), has referred to this success as the ‘Portuguese miracle’. The progress can be attributed to establishing a coherent public policy, implementing major reforms in the legal and institutional frameworks, and practicing sound strategic planning (Alegre et al., 2020). This implementation involved an overall perspective integrating various components, such as strategic planning, legislation, institutional framework, governance systems, introducing competition¹, access targets and quality of service goals, tariff and tax policy, labour force qualification, information publishing, promotion of research and development, and construction of the infrastructure (Baptista, 2014a).

¹Given the natural monopoly characteristics of the water industry, the concept of competition needs to be clarified. Baptista (2014a) refers to it as “virtual competition”. The benchmarking among utilities as well as the introduction of different models of governance have enabled competition to increase and ultimately the efficiency and quality of the services to improve.

The rising financial inflows that supported the structural transformations of the Portuguese water sector were motivated by the entry to the European Union in the 1990s. The European integration clearly accelerated the reversal of the state's authority over the financial sector, stimulating the creation of a private banking system. The wave of privatisations across the Portuguese economy was led by the development of capital markets in the new robust banking sector, and significant investments were made in the water sector with the help of external financing (Teles, 2015). During the time of the Strategic Plan for Water Supply and Wastewater Services (PEAASAR I) from 2000 to 2006, Portugal invested between 5 and 6 billion euros in construction, expansion, or rehabilitation of infrastructure for water supply and wastewater treatment (Alegre, 2010).

Until 1993, the local municipalities were exclusively responsible for the provision of water. The only exception was the state-owned utility EPAL (Empresa Pública de Águas de Lisboa), which supplied Lisbon. The Decree-Law no. 372/93 instituted the participation of private capital in the sector through concessions. The sector's property remained with the State, but, in many cases, the management was given to the private sector, which was supposed to bring more investments, mainly from European funds (Pato, 2011). Water supply and wastewater management were divided into bulk and retail services as part of the sector's corporatization process. Bulk or wholesale companies are capital-intensive and multi-municipal. They include water abstraction, treatment, lifting, and abduction, while retail services include storage and final distribution to end-consumers. The retail utilities are also in charge of tariff setting and collection.

Regarding wastewater services, bulk companies are responsible for wastewater elevation, transport, treatment, and disposal (ERSAR, 2021a). The municipalities remained as minor shareholders of the multi-municipal bulk companies, but their actual control was then limited to the retail sector. The central state concentrated investment efforts in the bulk sector, so several municipal concessions were created to enable the entry of private capital to support the needs of retail systems. Under those concessions, celebrated as public-private partnerships, the municipalities leveraged the investment capacity without jeopardising their control. The rural population in Portugal's most remote locations was the socioeconomic category that, in relative terms, gained the most from the water sector's investments. Moreover, the introduction of private capital to enable investments in retail utilities benefited large construction companies that received generous contracts for infrastructure projects and, in many cases, managed to acquire the retail concessions (Teles, 2015).

There are now three main options available for managing Portuguese water utilities: direct management, delegation and concession. Municipalities and associations of municipalities control and run the water services under the direct management model, often without the involvement of private businesses. The delegation model is applicable to parishes, user organisations, municipal companies or companies created in collaboration with the State (municipal or state utilities). Without a concession agreement, the State (central, local or both) owns and controls the utility directly under the delegation system. In this case, a contract of management must be signed, defining goals and tariff policies for the operator. In the concession model, a public-private partnership with municipalities and other private operators is created under a long-term contract, often ranging from 30 to 50 years. Private capital may participate primarily through the delegation and

concession models, and subsequently through direct management in cases of partnerships with the government or local governments (Marques and Berg, 2011; Pérez et al., 2019; ERSAR, 2021a).

Carvalho and Marques (2016) explain that the water and wastewater sectors in Portugal present a clearly unique market structure. Only a few nations, like Belgium, The Netherlands, and Romania, have separate wholesale and retail marketplaces. The retail water sector in Portugal is highly fragmented, with a large number of utilities, which is partially explained by the fact that the municipalities handle the majority of the services. The direct management of water provision is currently adopted by 158 municipalities (68% of the total), but these utilities cover only 26% of the population, being more frequent in rural areas with lower population densities. Another type of direct management occurs when a self-managed utility is created under the ownership of one or more municipalities. This model covers 22% of the population in Portugal. Although the utilities using the direct management model still prevail in the retail water sector, there has been a trend toward corporatisation of the sector in the last two decades. At the beginning of the 2000s, the concession and delegation management models counted only for 20% of the population, while today, they account for around half, more than doubling their share in the sector (ERSAR, 2021a).

Various research projects have looked at the market structure of the Portuguese water sector. Marques (2008), Correia and Marques (2011) and Marques and Simões (2020) studied Portugal's general efficiency of public and private utilities. In all those studies, the results favoured private utilities compared to public ones. The possibility of scale economies in eventual mergers and scope economies by integrating water and wastewater systems have been also examined. Correia and Marques (2011) found increasing returns of scale and decreasing economies of scope, suggesting that there are no advantages in the joint production of water and wastewater activities. Marques and De Witte (2011) concluded that the number of retail water utilities in Portugal should be reduced from more than 200 to around 60 to operate at the optimal scale. As a result, each utility should serve an average population of between 160,000 and 180,000 people.

Regarding scope, this study did not recommend joint activities of water and wastewater by the same utility. Pinto et al. (2017c) identified 40,000 customers as the optimal scale for water utilities. Carvalho and Marques (2016) and Marques and Carvalho (2014) also pointed out opportunities for economies of scale. Moreover, these studies identified some opportunities for merging bulk and retail operators and water and wastewater activities. Carvalho and Marques (2014) concluded that there are economies of vertical integration between wholesale and retail activities and economies of scale in water utilities. However, diseconomies of scope were found, suggesting that the utilities should choose only one specialisation between water and wastewater activities. Marques and Berg (2011) investigated how regulatory contracts for infrastructure deal with risk. They concluded that risk is a major concern when the public and private sectors collaborate and must be addressed in regulatory contracts. Tariff structure (Pinto and Marques, 2015; Marques and Berg, 2011; Martins et al., 2020, 2013; Gonçalves et al., 2014; Silvestre and Gomes, 2017), quality of service (Pinto et al., 2017a; Duarte et al., 2009) and sustainability (Pérez et al., 2019; Mergoni et al., 2022) have also been relevant themes of study in the water market in Portugal.

The establishment of a regulatory entity for the sector made mandatory the use of market-oriented management practices. The Water and Waste Services Regulation Authority (ERSAR), the regulating body for the whole water and waste industry, was created in 2009 after being founded in 1995 as the Supervisory Commission for Concessions. ERSAR's role rests on the idea that a natural monopoly should be controlled to guarantee proper protection to costumers, but keeping the market efficiency (Santos et al., 2018). Sunshine regulation has been adopted by ERSAR as an incentive for the utilities to improve their performance and has been addressed by several studies (e.g. Gonçalves et al., 2014; Marques, 2006; Marques and Pinto, 2018; De Witte and Marques, 2010a; Cardoso et al., 2012). Following the sunshine regulation model, a set of comprehensive performance measures is established and collected by ERSAR from utilities operating in the sector, and their outcomes are made available to the public. Since the regulator is not actively involved in the pricing formulation process, ERSAR's authority is not coercive (Gonçalves et al., 2014). In Portugal, sunshine regulation can be a particularly suitable approach due to the high inefficiency levels and the fragmented structure of the Portuguese market. Besides that, this practice can help minimise the existing political interference in the sector and increase transparency. Portugal faces the challenge of improving the performance of its utilities, which cannot be accomplished solely by publicising performance indicators (Marques, 2006). Thus, a structured methodology is needed to tackle this challenge, which supports the relevance of this study.

7.2.3 Asset management practices in the Portuguese water sector

The sustainable management of water infrastructure in Portugal has become a prominent issue in recent years and has resulted in various measures. The Decree-Law 194/2009, effective in 2013, required the existence of an asset management system in all water supply services and urban wastewater management services serving 30,000 people and above. In response to this law, ERSAR, jointly with LNEC (*Laboratório Nacional de Engenharia Civil* - National Civil Engineering Laboratory) and the Technical University of Lisbon, released technical guidelines that described a framework for integrated asset management. Several relevant research and collaboration projects have been conducted at the national and international levels as a result of LNEC's active leadership in asset management research, development, training and awareness efforts. Additionally, many utilities were used to test and design a decision support software for asset management. Portugal has hosted several conferences, seminars, courses and meetings on this subject. There has also been an intense activity on academic training, as shown by the recent development of multiple master and doctorate dissertations on this topic at Portuguese universities. For more detail on this process, see Matos and Baptista (1999), Alegre (2010), Leitão et al. (2016) and Amaral et al. (2017).

Alegre et al. (2020) highlighted that the primary goal of the reform process, started in 1993, was the creation of new infrastructures to improve the availability and quality of services. However, in recent years the focus has been shifted toward the value maximisation of existing infrastructures in a long-term perspective to ensure sustainable service delivery. The massive investment

of 13 billion Euros from 1993 to 1999 was mainly applied to bulk systems, which is noteworthy given the country's population of approximately ten million. The significant asset portfolio generated by this spending has a high value, although some assets are too old, complex and demanding in management. Therefore, effective asset management is a priority to ensure that the value of these assets is maintained and sustainable water services are provided.

In 2015 a new strategic plan for the water sector, the PENSAAR 2020 (*Plano Estratégico de Abastecimento de Água e Saneamento de Águas Residuais* - Strategic Plan for Water Supply and Wastewater Sanitation 2020), was launched bringing the management of the sectors' assets to the centre of the discussion. As explicitly stated in the Plan: "The strategy should be less centred in new infrastructures to increase the served population and focuses more on the management of the sector assets, its operations and the quality of the provided services with an overall sustainability" (Frade et al., 2015). The plan determines five strategy axis, being Axis 3 dedicated to the optimisation and efficient use of the existing resources. This axis establishes six operational objectives, as follows: (i) optimisation of the installed capacity use and increase of service adhesion; (ii) reduction of physical water losses; (iii) control of rainwater to foul sewerage; (iv) efficient management of assets and rehabilitation increase; (v) upgrade resources and sub products; (vi) allocation and efficient use of the water resources.

The control of water losses, one of the objectives of Axis 3 of PENSAAR 2020, is commonly researched in this field. According to the study conducted by EurEau (2021), Portugal experiences a high rate of water losses, with an estimated 30% of the total water supply being lost. Marques and Monteiro (2001) indicated a critical low level of asset rehabilitation and non-existence of preventive maintenance as the responsible for the considerable volume of water losses. Those authors suggest a set of indicators to monitor and control water losses. Marques and Monteiro (2003) also reinforce that the high volume of water losses in Portugal is associated with the focus on building new assets instead of giving more attention to the existing systems' operation and maintenance. This study also recommends the application of performance indicators to control losses. The minimisation of water losses is discussed by Machado et al. (2009) that reports a case study in a bulk water system. The use of energy resources is the focus of the research conducted by Loureiro et al. (2020) that proposed a comprehensive framework assessment for energy efficiency and concluded that energy inefficiencies are related to water losses or network layout, not to pumping inefficiencies.

The rehabilitation of water assets is considered vital in increasing the efficiency of water utilities. Ferreira and Carriço (2019) analysed practical applications of asset management approaches by comparing alternatives for rehabilitation strategies employing performance indicators. It was found that decreasing proactive management spending may result in future problems and unanticipated costs. A case study describing rehabilitation of infrastructures in a utility in the Algarve region is described by Cabral et al. (2019), and the results indicate that the assets' economic valuation accuracy is essential to determine a rehabilitation strategy. The application of a performance assessment framework for water systems tested in two Portuguese retail water utilities by Santos et al. (2022) identified vulnerable areas to flooding and the need for rehabilitation investments.

Carriço et al. (2012) developed a methodology to prioritise rehabilitation interventions, using the technique ELECTRE III.

The current situation underlined by PENSAAR 2020 displays an inadequate rehabilitation rate, lack of asset knowledge and difficulties in ensuring cost recovery. For the current rehabilitation rates to be sustainable, pipes would need to last, on average, 100 and 200 years for water and wastewater networks, respectively. There are also serious problems of economic and financial sustainability. Over 3.5 million people, or 33% of the country's population, are served by utilities that do not ensure cost recovery. A large number of utilities are not able to quantify the actual cost of their services. The strategic plan also addresses new tariff regulations and utility mergers (Amaral et al., 2017).

The development of a strategy to implement effective asset management systems is also at the core of PENSAAR 2020's Axis 3. Those methodologies should complement and support the approach initiated by ERSAR and LNEC. In that sense, the structured procedure developed by Cardoso et al. (2012) include elements of strategic, tactical and operational planning. It was tested in four operators with different characteristics, focusing on the diversity of the utilities to ensure flexibility.

Leitão et al. (2016) presented the results of a collaborative project led by LNEC comprising asset management system implementations in 19 retail water utilities, covering different sizes, management models and scope (water, wastewater, storm water). The utilities took advantage of the simultaneous implementation process by sharing difficulties and solutions, and at the end, they could successfully develop their own strategic and tactical plans. This process proved to be successfully suited for the water industry scenario in Portugal and many of the strategic and tactical plans developed were actively applied to the systems.

The water systems in Portugal show highly diverse results in terms of asset management performance. The results of a survey conducted by the *Specialised Commission for Asset Management* from the *Portuguese Association for Water Distribution and Drainage (Associação Portuguesa de Distribuição e Drenagem de Águas - APDA)* in 2019, using data from bulk and retail utilities, indicate that asset management practices are not used by 54% of those utilities. Asset management goals are not established by 41% that declare to have implemented an asset management system. Besides that, 57% of those utilities do not dedicate personnel exclusively to asset-related activities. Many of those utilities do not perform preventive maintenance, do not analyse their assets' condition and record their data on paper and spreadsheet records (APDA, 2019). Amaral et al. (2017) mention the highly fragmented market structure, the politicised nature of municipal water utility management and the existing accounting procedures as some of the main barriers to spreading asset management best practices. When discussing the applicability of asset management to small and medium utilities, Alegre (2010) reinforces the option to establish realistic targets and network connections with relevant peers for sharing problems and solutions.

Benchmarking studies have been undertaken in Portugal employing asset management elements. Santos et al. (2022) performed a comparison assessment of two Portuguese retail utilities, using a multi-dimensional performance framework, where infrastructural sustainability is one of

the examined dimensions. The results show the potential of an assessment framework to support planning and monitoring of activities and investments.

Targets for asset management were also proposed by Ferreira and Carriço (2019), that performed a case-study in a water supply system in Lisbon. This study evaluated the operator's performance in fulfilling the proposed tactical objectives by the use of thirteen metrics.

The comprehensive set of metrics that ERSAR annually requests from the sector's retail operators under the sunshine regulation strategy enables a multifaceted assessment of utilities' performance. Those metrics were already employed to undertake benchmarking studies in the literature. Pinto et al. (2017a,c) used those metrics to evaluate *quality of service*; Henriques et al. (2020) assessed the *general performance of wastewater operators*, Mergoni et al. (2022) evaluated *environment achievements* and Amaral et al. (2022) addressed the *techno-economic efficiency* of wastewater utilities using ERSAR's metrics. The study developed by Vilarinho et al. (2023c) selected metrics related to asset management practices to construct composite indicators following the BoD approach. The role of the environment was also examined including contextual variables. However, that study focused on wholesale utilities, a different market, and emphasised the progress of utilities along a five-year period. This study aims to extend the developments of that research by focusing on the retail water market and the role of the context is also explored. More importantly, the use of ERSAR's metrics to identify peers and targets for the retail water operators in asset management performance represents the main innovative contribution of this work. The relevance of this study relies on the need for immediate actions due to the unsatisfactory water infrastructure conditions, both in Portugal and worldwide, from which considerable room for improvement can be noticed.

7.3 Methodology

The proposed methodology includes three stages covering the development of the BoD methods employed in the study. First, the standard computation of the CIs using a deterministic approach is presented. The techniques employed to determine the peers and targets are explained in the second stage. Finally, the robust and conditional methods are discussed.

7.3.1 Calculation of the standard deterministic composite indicator

This subsection explains how the composite indicator can be computed using the standard deterministic BoD model. The standard deterministic CI, which is the baseline method used to calculate the composite indicators, is described in this subsection. BoD linear programming models and the metrics aggregated as outputs are employed to generate the CIs.

The BoD Model (7.1) is used when only desirable metrics are aggregated. Desirable metrics are the ones that are targeted to increase, so better performance results correspond to higher values. On the contrary, lower values are preferable for undesirable metrics.

$$\begin{aligned}
& \text{maximise} \quad \beta_{j_0} \\
& \text{subject to} \quad \sum_{j=1}^n y_{rj} \lambda_j \geq y_{rj_0} + g_y \beta_{j_0} \quad r = 1, \dots, s \\
& \quad \quad \quad \sum_{j=1}^n \lambda_j = 1 \\
& \quad \quad \quad \lambda_j \geq 0, \quad j = 1, \dots, n \\
& \quad \quad \quad \beta_{j_0} \in \mathbb{R}
\end{aligned} \tag{7.1}$$

The BoD Model (7.2) based on the Directional Distance Function (DDF) and introduced by Zanella et al. (2015) is employed to handle both desirable and undesirable metrics.

$$\begin{aligned}
& \text{maximise} \quad \beta_{j_0} \\
& \text{subject to} \quad \sum_{j=1}^n y_{rj} \lambda_j \geq y_{rj_0} + g_y \beta_{j_0} \quad r = 1, \dots, s \\
& \quad \quad \quad \sum_{j=1}^n b_{kj} \lambda_j \leq b_{kj_0} - g_b \beta_{j_0} \quad k = 1, \dots, l \\
& \quad \quad \quad \sum_{j=1}^n \lambda_j = 1 \\
& \quad \quad \quad \lambda_j \geq 0, \quad j = 1, \dots, n \\
& \quad \quad \quad \beta_{j_0} \in \mathbb{R}
\end{aligned} \tag{7.2}$$

BoD Models (7.1) and (7.2) are presented in their envelopment formulation, often employed in peer identification for benchmarking purposes. In the BoD models, y_{rj} represents the desirable metrics, whereas b_{kj} represents the undesirable ones. r is an index for desirable metrics, ranging from 1 to the total number of desirable metrics s , while k represents each undesirable metric, ranging from 1 to the total number of undesirable metrics l . The parameters y_{rj_0} and b_{kj_0} are the values of desirable and undesirable metrics observed for the DMU j_0 under assessment.

The BoD model must be solved n times, where n represents the number of assessed DMUs. For each DMU under evaluation denoted as j_0 , the values of the decision variables λ_j and β_{j_0} are obtained as the solution of the BoD model. The variable β_{j_0} represents the factor by which the desirable metrics should proportionally increase and the undesirable metric should proportionally decrease toward the best-practice frontier. Note that the model's objective function aims to max-

imise β_{j_0} , by finding the optimal results for the DMU under assessment. As discussed by Lavigne et al. (2019), the values of λ_j identify how relevant other DMUs are for representing the benchmark against the DMU under assessment. Therefore, λ_j different from zero identify the peers; the higher their values the more relevant the peer is.

The direction of expansion of the desirable metrics and reduction of the undesirable ones is indicated by the Directional Distance Vector defined as $(g_y, -g_b)$. The direction vector used in DEA and BoD models is a crucial factor that can impact the calculated scores. To address this issue, various solutions have been proposed in the literature, depending on the research objectives. Fried et al. (2008) and Rogge et al. (2017) have discussed different options for selecting the direction vectors in DEA and BoD models. In this study, the values of $(g_y, -g_b)$ were used as $(y_{rj_0}, -b_{kj_0})$, following Zanella et al. (2015) and Rogge et al. (2017), so that each DMU may guide its improvement using the values of its own performance metrics. This results in a proportional interpretation of the composite indicator value.

Since the maximum feasible level of β_{j_0} is obtained by optimisation, DMU j_0 under assessment is given the best possible results. The CI for j_0 is calculated as $1/(1 + \beta_{j_0})$. The best-performing DMUs are located in the best-practice frontier, meaning that for those DMUs neither the reduction of undesired metrics nor the expansion of desirable metrics is required. For those instances, the obtained score for β_{j_0} equals zero, and for CI_{j_0} is equal to 1. For all the other cases in the deterministic approach, β_{j_0} is a positive number, meaning that CI_{j_0} ranges from 0 to 1.

7.3.2 Determination of peers and targets for benchmarking

This subsection explains how the peers and targets are obtained in the standard deterministic BoD model. The first set of constraints, one for each s desirable metric, in Models (7.1) and (7.2) are shown in expression (7.3).

$$\sum_{j=1}^n y_{rj} \lambda_j \geq \underbrace{y_{rj_0} + g_y \beta_{j_0}}_{\text{Target}} \quad r = 1, \dots, s \quad (7.3)$$

For each r desirable metric, the right-hand side term of expression (7.3) is the sum of the observed desirable metric of the DMU under assessment y_{rj_0} and its expansion toward the best-practice frontier $g_y \beta_{j_0}$. Therefore we can say that $y_{rj_0} + g_y \beta_{j_0}$ defines the target for each desirable metric that DMU j_0 should have to reach the best-practice frontier.

Following the same rationale, the targets for the undesirable metrics are displayed in the set of l constraints in (7.4) taken from Model (7.2). The values of each undesirable metric b_{kj_0} are subtracted by $g_b \beta_{j_0}$, representing each indicator's contraction toward the best-practice frontier.

$$\sum_{j=1}^n b_{kj} \lambda_j \leq \underbrace{b_{kj_0} - g_b \beta_{j_0}}_{\text{Target}} \quad k = 1, \dots, l \quad (7.4)$$

If there are no undesirable metrics, such as displayed in (7.1), the calculation of the targets is conducted only using expression (7.3).

The linear programming model generates a vector of values of λ_j ($j = 1, \dots, n$) for each DMU under evaluation. The peers of DMU j_0 are the DMUs that present λ_j different from zero, and their obtained intensity values highlight their role in the benchmarking exercise.

7.3.3 Use of robust and conditional approaches for composite indicators

This section explains how CIs are generated, and peers and targets are determined using the robust and robust conditional (or simply conditional) approaches.

The robust approach for computing composite indicators was developed to overcome the high sensitivity that the deterministic technique displays in presence of outliers and atypical observations in the sample. The conditional approach is employed to provide adjustments to the CIs by accounting for the influence of external contextual variables. Those techniques have been developed initially by Cazals et al. (2002) and Daraio and Simar (2005, 2007a), and have been employed and extended by numerous research such as De Witte and Kortelainen (2013); Rogge et al. (2017); De Witte and Schiltz (2018); Lavigne et al. (2019); D’Inverno and De Witte (2020); Fusco et al. (2020); Mergoni et al. (2022).

The robust method for estimating CIs involves computing a BoD model many times using randomly selected sub-samples from the collection of DMUs instead of doing so only once as the deterministic approach. This sampling procedure, known as bootstrapping, is performed with replacement, meaning that each unit can be drawn many times in the same sample. The number of sub-samples, denoted as B , is often a very high number, large enough to minimise the effect of outliers in calculating averages. The arithmetic average of the several CIs ($CI_{j_0}^{b,m}$) produced for each sub-sample yields the final robust CI for a given DMU. The effect of extreme values will be mitigated in the computation of the average CI, because they will be not present in all the sub-samples. The resulting robust CI, referred as $CI_{j_0}^m$, is expressed by (7.5).

$$CI_{j_0}^m = \frac{1}{B} \sum_{b=1}^B CI_{j_0}^{b,m} \quad (7.5)$$

It is possible that the DMU being evaluated (j_0) is not included in the sub-sample used for BoD calculation, and that this DMU is better-performing than all the DMUs in the sub-sample. In this case, $\beta_{j_0}^{b,m}$ displays a negative value and the value of $CI_{j_0}^{b,m}$, obtained from the expression $1/(1 + \beta_{j_0}^{b,m})$, does not express the proportional performance improvement expected for a better-performing DMU. Besides that, if $\beta_{j_0}^{b,m}$ is lower than -1, $1/(1 + \beta_{j_0}^{b,m})$ can assume negative values, and if β_{j_0} equals -1, CI cannot be obtained. This situation does not reflect the “super-performing” nature of those DMUs. Following Mergoni et al. (2022), we employ an alternative way to compute $CI_{j_0}^{b,m}$, when $\beta_{j_0}^{b,m}$ is negative, in order to solve this problem. This alternative solution is shown in (7.6).

$$CI_{j_0}^{b,m} = \begin{cases} \frac{1}{1+\beta_{j_0}^{b,m}}, & \text{if } \beta_{j_0}^{b,m} \geq 0; \\ \log_{10}(1 - \beta_{j_0}^{b,m}) + 1, & \text{if } \beta_{j_0}^{b,m} < 0 \end{cases} \quad (7.6)$$

The conditional approach accounts for the contextual variables in the computation process, allowing the CIs to be adjusted by comparing the DMUs with more similar units. In that sense, fairer evaluations can be performed. As in the robust approach, B sub-samples of size m are collected, but not randomly. The sub-sample collection is performed according to a similarity function. A kernel function developed according to the contextual factors is employed to estimate the similarity between the DMU under evaluation and the other DMUs. The context can be characterised using continuous or categorical variables that can be included in the same model (Li and Racine, 2003). The BoD model is solved B times for each DMU j_0 and the CIs for each sub-sample b , designated as $CI_{j_0}^{b,m,z}$, are computed according to the expressions shown in (7.6). The average of $CI_{j_0}^{b,m,z}$ for a total of B sub-samples represents the conditional CI, as indicated in (7.7).

$$CI_{j_0}^{m,z} = \frac{1}{B} \sum_{b=1}^B CI_{j_0}^{b,m,z} \quad (7.7)$$

The influence of the contextual variables can be assessed by looking at the score ratio between the robust CI and the conditional CI ($CI_{j_0}^m / CI_{j_0}^{m,z}$). Using non-parametric regression between the score ratios and the contextual variables, partial plots with bias-corrected bootstrapped non-parametric confidence intervals can be obtained. Confidence intervals that don't overlap reveal a statistically significant relationship between the contextual variable and the utilities' performance (see also D'Inverno et al., 2021).

A significantly higher score ratio for a given level of the contextual variable indicates that the context is more favourable for better performance at this level. This happens when the conditional and the robust scores are similar, that is, irrespective of whether the unit under evaluation is compared against more similar units or not.

In the case of the robust and conditional BoD approaches, a set of λ_j values is generated for each computation. In each of the B computations, a number of DMUs for which λ_j is different from zero can be identified as a peer for the DMU under assessment. This makes the number of peers in those approaches to increase significantly compared to the standard BoD approach. As previously discussed, the relevance of a peer for benchmarking purposes increases as the intensity value λ_j increases. Lavigne et al. (2019) explain that the most relevant peers in the case of robust and conditional approaches are given by the higher average values of λ_j in B samples collected.

7.4 Case study

This section presents the data used in the study in three parts. The first one (subsection 7.4.1) presents the metrics used for the construction of two different and complementary composite in-

dicators (CIs). The second part (subsection 7.4.2) details the dataset used to build the composite indicators (CIs). Finally, the third part (subsection 7.4.3) presents the data about the exogenous variables employed to characterise the context.

7.4.1 Metrics employed for the composite indicators (CIs)

The metrics utilised to construct the CIs in this study are described in this subsection.

Two distinct composite indicators are created by combining those metrics. The strategy for developing two different indicators is justified by the fact that improvements in managerial aspects of asset management usually take some time to generate operational benefits in a utility's performance (Luís and Almeida, 2021). Therefore, one of the CIs reflects the business's observable operational achievement: the *Resource and Infrastructure Sustainability Index (RISI)*. On the other hand, the evolution of the management system maturity is assessed by the *Asset Management Maturity Index (AMMI)*. These two composite indicators have been introduced by Vilarinho et al. (2023c), but used to assess the Portuguese wholesale utilities and to provide a different empirical analysis.

The *Resource and Infrastructure Sustainability Index (RISI)* is composed by the metrics: pipeline rehabilitation (AA09b), occurrence of pipeline failure (AA10b), actual water losses (AA12b) and energy efficiency in pumping stations (AA13b). All the data reported by the water operators to ERSAR have been analysed in order to choose the metrics. In line with the literature review, which emphasises the importance of water losses, mains failure, mains rehabilitation and energy usage for managing infrastructures in water systems, those metrics have been selected to compose the RISI. They comprise the information on the operational performance of the utilities' assets reported to ERSAR and reflect the tangible results of asset management. The definition of the four metrics and their units of measurement are displayed in Table 7.1. The letter "b" presented in all ERSAR's metric codes indicates that the metrics come from retail utilities ("baixa" in Portuguese) to distinguish from the metrics collected from wholesale utilities that present the letter "a" ("alta" in Portuguese).

The annual report issued by ERSAR (ERSAR, 2021a) presents the results of the main performance metrics and their general reference values. ERSAR determines the reference values for the metrics that compose the RISI in three levels: good, medium and unsatisfactory. This study considers the "good" or desirable level as the ERSAR's goal for the utility.

The metric *Pipeline Rehabilitation (AA09b)* is the average yearly percentage of pipelines with an age greater than ten years undergoing rehabilitation during the previous five years. This metric aims to determine whether there is a continuous practice of pipeline restoration to guarantee their continuous renewal and an acceptable average age of the network. ERSAR defines this metric as higher than 1%, with a good result between 1% and 4%. Values above 4% are considered medium. However, the pipeline networks in Portugal are, on average, far from being at a good level, with the average result for the retail water utilities being at most 0.6% in all years from 2016 to 2020.

The second metric in RISI is the *Occurrence of Pipeline Failure (AA10b)*, which is intended to evaluate the occurrence of pipeline faults that can cause water losses and potential supply interruptions. It measures the number of failures per 100 km of pipelines per year. ERSAR considers a positive (“good”) outcome for this metric to be less than 30 occurrences per 100 kilometres per year. Retail operators had an average of 38 to 42 between 2016 and 2020, regarded as a medium level.

The metric *Actual Water Losses (AA12b)* assesses the water losses in leakages and overflows, defined as the daily volume of real losses divided by the extension of the utilities’ pipelines. ERSAR collects this information using two different units of measurement. This metric is expressed in litre per branch per day for denser pipeline networks, with more or equal to 20 connection branches per kilometre. If the pipeline network density is inferior to 20 branches per kilometre, the water losses are measured in cubic meters per kilometre per day. According to ERSAR, the good result for water losses is lower than 100 litres per branch per day for the denser-network utilities and inferior to 3 cubic meters per kilometre per day for the remaining utilities. According to these limits, the actual losses in Portugal are at the medium level for the less dense networks ranging from 125 to 137 litres per branch per day from 2016 to 2020. For high-density utilities, the average performance in water losses is better. This average was 2.6 cubic meters per kilometre per day in 2020. In this study, the variable density of branches per kilometre of a pipeline, collected by ERSAR with the code PiAA01b, was employed to transform the units of measurement, enabling all the water loss data to use the same unit. Because most utilities present a density superior to 20 branches per kilometre, all the data were converted to litres per branch per day.

The fourth metric that composes RISI is the energy efficiency in pumping stations (AA13b). This metric aims to assess the use of energy resources by the management entities. It is defined as the average normalised energy consumption of the pumping facilities. The performance may be judged as medium up to a value of 0.54 kilowatts per year per 100 meters elevation; however, the good performance result may be at most 0.4.

The second CI developed for asset management measurement is the *Asset Management Maturity Index (AMMI)*. The AMMI is composed by two metrics: the *Infrastructure Knowledge Index (PAA31b)* and the *Infrastructure Asset Management Index (PAA32b)*. Those are the only metrics that reflect managerial elements directly related to asset management in the dataset collected by ERSAR. They were selected because they are the two critical facets of managing infrastructures in water systems, (1) the knowledge about the assets and (2) the organisational systems that were implemented.

The *Infrastructure Knowledge Index* expresses the level of knowledge that the utilities hold about their assets. It is measured as a score taken from a questionnaire issued by ERSAR, using a scale from 0 to 200. This metric deals with the existence of engineering drawings and other records, as well as detailed information about asset conservation and the interventions performed. This information is crucial for water supply operators’ business, considering that part of water systems’ assets is buried and constructed to last for many years.

The second metric that composes the AMMI is the *Infrastructure asset management index*,

which reflects the features of the management systems that the water utilities have implemented. The *Infrastructure asset management index* is also measured using the scores taken from a questionnaire issued by ERSAR on a scale from 0 to 200. The questionnaire used to generate the *Infrastructure asset management index* deals with the utilities' management systems, assessing aspects such as general asset management framework, strategic, tactical and operational planning, documentation and communication. The elements included in the questionnaire used for the computation of the *Infrastructure asset management index* are inspired by the international standard for asset management, the ISO 55001 (ERSAR and LNEC, 2017). Table 7.1 displays the metrics that compose AMMI with their definition and the codes employed by ERSAR.

7.4.2 Data used for building the composite indicators

This subsection details the data employed to build the two proposed composite indicators: the RISI (Resource and Infrastructure Sustainability Index) and the AMMI (Asset Management Maturity Index).

Pipeline Rehabilitation (AA09b) is a desirable metric for the metrics employed for the RISI. On the other hand, *Occurrence of Pipeline Failure (AA10b)*, *Actual water losses (AA12b)* and *Energy Efficiency in Pumping Stations (AA13b)* represent undesirable metrics. For the AMMI, the *Infrastructure Knowledge Index (PAA31b)*, and the *Infrastructure Asset Management Index (PAA32b)* are desirable metrics.

The research includes indicators acquired by ERSAR and widely publicised on the regulator's website in line with the sunshine regulation policy. ERSAR has regularly reviewed its assessment system and the indicators that make it up to ensure they are consistent with its strategic goals. This study looked at the third generation of indicators, which covered the years 2016 through 2020, and selected the data from 2020 to perform the benchmarking assessment².

A list of 233 water utilities at the retail level may be found in the ERSAR dataset for 2020. The dataset is incomplete since many utilities have not reported their results, and multiple missing data are present. The operators included in the sample studied were only those who have provided data for at least two metrics used in the RISI and presented no missing data in the metrics of AMMI. This approach guaranteed the consistency and practical relevance of the obtained results. We removed ten utilities from the original sample, resulting in a final number of 223 water operators for evaluation³. Even after removing these utilities, the remaining sample still accounts for 95.7% of the total number, representing a significant proportion of the original dataset. The remaining missing data instances were treated following the procedure employed by Kuosmanen et al. (2002), Morais and Camanho (2011) and Henriques et al. (2020). For the desirable metrics, a small value equal to the minimum value of each metric replaced the missing data. In the case of undesirable metrics, the missing instances were changed to a large number equivalent to the maximum value

²The data is available in ERSAR's website: <https://www.ersar.pt/pt/site-publicacoes/Paginas/edicoes-anuais-do-RASARP.aspx>.

³The utilities removed from the sample for presenting missing data are: APIN, CM de Cabeceiras de Basto, CM de Caminha, CM de Idanha-a-Nova, CM de Marco de Canaveses, CM de Monchique, CM de Paredes, CM de Santo Tirso, CM de Vila Nova de Paiva, and CM de Vila Viçosa.

of each metric. This procedure ensures that the DMU cannot benefit from the lack of data for its performance evaluation. Several scores of the *Infrastructure Asset Management Index*, one of the AMMI's components, present a value of zero in 2020. This fact reflects the low level of maturity in many retail water utilities concerning the development of management systems. The same situation occurs for the metric *Pipeline Rehabilitation*, one of the RISI components, meaning that those utilities could not recover their pipelines as expected.

However, a few utilities presented zero *occurrences of failures in pipelines*, which is another component of the RISI and represents the best result for this undesirable metric. In general, DEA formulations require that the inputs and outputs are positive. Even though, this “positivity property” can be relaxed, as detailed by Charnes et al. (1991), we chose to replace the zero values with 0.01, a small positive number as recommended by Bowlin (1998) and discussed by Sarkis (2007). Since the BoD model emphasises the indicators for which the DMU performs best, an indicator with a minimal value would not be expected to contribute to any bias in the efficiency assessment. Table D.1 in Appendix D.1 displays the list of the evaluated utilities (DMUs) with the identification codes used in the study ranging from B1 to B223.

Table 7.1: Metrics for constructing the composite indicators.

CI	Metric Code	Metric description	Metric definition	ERSAR's goals	N	Average	St. Dev.	Min.	Max.
RISI	AA09b	Pipeline Rehabilitation (%/year)	Average annual percentage of pipelines with life higher than ten years rehabilitated in the last five years.	≥ 1	223	0.58	0.86	0.01	5.40
	AA10b	Occurrence of Pipeline Failure ($n^\circ / 100 \text{ km} \cdot \text{year}$)	Number of failures in pipelines per 100 km in a year.	≤ 30	223	53.12	70.30	0.01	350.00
	AA12b	Actual water losses (l/branch.day)	Actual water losses due to leakages and overflows per unit of pipeline length.	≤ 100	223	173.74	169.05	2.00	706.30
	AA13b	Energy efficiency in pumping stations ($\text{kWh}/\text{m}^3 \cdot 100\text{m}$)	Average normalised energy consumption of pumping stations.	≤ 0.4	223	1.71	1.27	0.35	3.24
AMMI	PAA31b	Infrastructure Knowledge Index (Score 0-200)	Evaluation score of the knowledge of the several infrastructures in different classes ranging from 0 to 200.	200	223	132.20	41.93	29.00	200
	PAA32b	Infrastructure Asset Management Index (Score 0-200)	Evaluation score in a questionnaire about asset management practices ranging from 0 to 200.	200	223	40.17	67.94	0.01	200

The descriptive statistics for the data related to the metrics that compose both CIs are presented in Table 7.1. Looking at the average results of the metrics in 2020 (Table 7.1) and comparing them with ERSAR's goals, the asset-management-related metrics perform worse than the ideal levels. In terms of the operational metrics, the average AA09b is less than 1%, the average AA10b is greater than 30, the average AA12b is much higher than 100 and the AA13b significantly surpasses 0.4. The managerial metrics also indicate poor average outcomes. PAA31b and PAA32b are far below the ideal score of 200. The benchmarking exercise performed in this study indicates realistic targets for the operators to pursue, in comparison with the market best-performs. Given this scenario, such targets may not always reach the expected goals set by ERSAR.

7.4.3 Data used as exogenous variables

This subsection presents the data employed to characterise the environment in which the utilities under evaluation operate.

Contextual factors were selected among the data reported by the retail water utilities to ERSAR to characterise the environment in which the utilities operate. Four contextual variables or exogenous variables were chosen: the management system, the typology of intervention area, the geographic location and the volume of activity.

The management system indicates the kind of utility ownership, according to the models available for the water sector in Portugal. Municipalities own and operate most retail water utilities directly, 74.4% in 2020. Direct management is thus the management system of 166 retail water utilities. The remaining 25.6% are divided in Concession (12.6%) and Delegation (13.0%).

The typology of intervention area is mainly related with the population density. According to the kind of intervention area, the water operators can be classified in urban, semi-urban or rural. Based on this criterion, most of the utilities (147) are rural, representing 65.9% in 2020. Other 55 utilities (24.7%) are considered semi-urban and only 21 (9.4%) utilities are urban.

The geographic location is based on the region of Portugal where the utility primarily operates. This classification is based on the European Union's Nomenclature of Territorial Units for Statistics (NUTS) standard. At its second level, known as NUTS 2, the locations presented in ERSAR's reports for mainland Portugal are Algarve, Alentejo, Centre, Lisbon and North.

The volume of activity expressed as the metric *PAA50b* represents the amount of water (in m^3) supplied by the operator in a year. This metric can be used as a proxy for the utility size and is available in ERSAR's reports. However, following Mergoni et al. (2022), we chose to characterise the context by classifying the utilities as small, medium and large. We use the approach of the *Drinking Water Directive*, Council Directive 98/83/EC (European Commission, 1998). This directive defines the limit between small and large utilities as 1,000 m^3/day of average supplied water volume or 5,000 persons in the population served. Small utilities were defined in this study as those that provide less than 1,000 m^3/day . Only 63 utilities fall under this threshold; thus, the remaining 160 operators were split into groups of 80 units each, including medium and large utilities.

Table 7.2 presents the statistics for the exogenous variables in 2020.

7.5 Results and discussion

This section presents and discusses the study's findings in three parts. The computation of composite indicators using the deterministic, robust and robust conditional approaches is presented in the subsection 7.5.1. Subsection 7.5.2 describes the identification of peers and targets for benchmarking practices. The role of the environment on the performance of the water utilities is discussed in subsection 7.5.3.

7.5.1 Composite Indicator results

The results from the calculation of the CIs are presented and discussed in this subsection.

The methods explained in subsections 7.3.1 and 7.3.3 are employed to compute the deterministic, robust unconditional and robust conditional CIs. BoD Model 7.2, which can handle both

Table 7.2: Categorical exogenous variables.

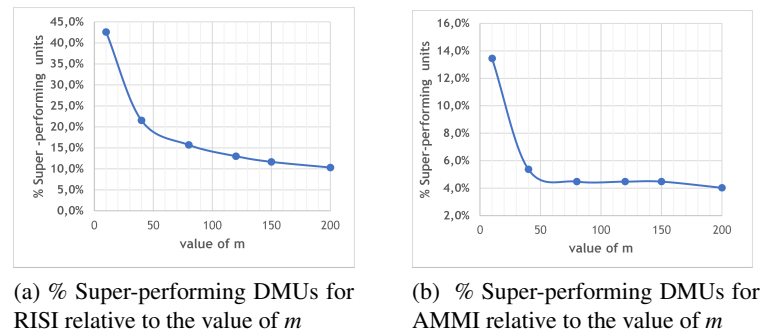
ERSAR Code	Variable Description	Categories	Obs.	Number of utilities and percentage per category
PAA02b	Management System	Concession,	223	Concession - 28 (12.6%)
		Delegation or		Delegation- 29 (13.0%)
		Direct Management		Dir. Manag. - 166 (74.4%)
PAA14b	Typology of Intervention Area	Rural areas,	223	Rural - 147 (65.9%)
		Semi-Urban areas		Semi-urban - 55 (24.7%)
		or Urban areas		Urban - 21 (9.4%)
NUTS2	Geographic Location	Alentejo,	223	Alentejo - 54 (24.2%)
		Algarve,		Algarve - 18 (8.1%)
		Centre,		Centre - 68 (30.5%)
		Lisbon or		Lisbon - 16 (7.2%)
PAA50b	Volume of Activity	North	223	Norte - 67 (30.0%)
		Small,		Small - 63 (28.3%)
		Medium		Medium - 80 (35.9%)
		or Large		Large - 80 (35.9%)

desirable and undesirable metrics, calculates the RISI. BoD Model 7.1 calculates the AMMI since this indicator only includes desirable metrics. The R program solved the BOD models using the R program's packages *Rglpk* (Theussl and Hornik, 2019) and *lpSolve* (Berkelaar et al., 2023). An additional R package, the *np* package (Hayfield and Racine, 2008), was used to handle the collection of sub-samples according to the similarity level of DMUs in the robust conditional approach. This R package was also used to compute the bias-corrected bootstrapped non-parametric confidence intervals of the utilities' performance concerning the environment.

For the robust and robust conditional CIs, the values of the parameters m and B must be determined. B is often a high number, and for this study, the value of 2,000 was employed for B . According to Daraio and Simar (2007a), there are no formal guidelines for choosing m , but for smaller values of m , the presence of numerous "super-performing units" might be problematic. Therefore a sensitivity analysis is recommended to select a value of m . Figure 7.1 shows two graphs that present the resulting percentage of "super-performing" DMUs in each of the robust CIs' computations for several values of m . These findings led to the choice of $m = 80$ for both CIs since, at this value, the proportion of "super-performing" units reduces, whereas it remains relatively stable at higher values.

The CI scores obtained with the deterministic, robust and robust conditional techniques are shown in Table D.1 in Appendix D.1 for all DMUs. Table 7.3 presents the descriptive statistics for both composite indicators. A close look at the average of both indicators reveals that the performance of the retail water operators in asset management may be significantly improved.

A combined visualisation model shown in Figure 7.2, based on the BCG (Boston Consulting Group) matrix, is displayed, following Vilarinho et al. (2023c), to enable the joint analysis of water operators in both indicators (RISI and AMMI). Considering that the robust conditional approach

Figure 7.1: Sensitivity analysis for m selection

provides the most accurate and fair comparison of the utilities, this version of the composite indicators was used to represent the performance of the utilities in the following analyses. The 2×2 matrix in Figure 7.2 divides the utilities according to the median of their robust conditional indicators. Figure 7.2 classifies the utilities' performance into four categories, as listed below, to show how they operate compared to their competitors:

- (i) Stars. These utilities present better operational results and better management systems than their peers. In this category, both RISI and AMMI are higher than the median values.
- (ii) Soldiers. This group takes care of the assets, keeping their operational conditions, but in comparison to their counterparts, the management procedures are not effectively established. For the Soldiers, the RISI is higher than the median while the AMMI is lower or equal.
- (iii) Infants. This category gives the initial moves in the organisation for asset management, and they show worse tangible results than their peers. The Infants present both RISI and AMMI below or equal to the medians of all utilities.
- (iv) Learners. Although these utilities have been working on effective management systems, they have performed poorly than most of their counterparts regarding operational results in asset management. This group's AMMI is above the median, while its RISI is equal to or lower than the median.

Table 7.3: Descriptive statistics for RISI and AMMI Results.

CI	CI Formulation	Average	St. Dev.	Min	Q1	Median	Q3	Max
RISI	Deterministic RISI CI (CI_{j_0})	0.697	0.161	0.529	0.535	0.656	0.818	1.000
	Robust Unconditional RISI CI ($CI_{j_0}^m$)	0.766	0.214	0.530	0.585	0.731	0.879	2.082
	Robust Conditional RISI CI ($CI_{j_0}^{m,z}$)	0.824	0.161	0.533	0.667	0.856	0.985	1.076
AMMI	Deterministic AMMI CI (CI_{j_0})	0.669	0.213	0.145	0.510	0.675	0.840	1.000
	Robust Unconditional AMMI CI ($CI_{j_0}^m$)	0.670	0.213	0.145	0.511	0.676	0.841	1.005
	Robust Conditional AMMI CI ($CI_{j_0}^{m,z}$)	0.719	0.218	0.148	0.562	0.741	0.925	1.001

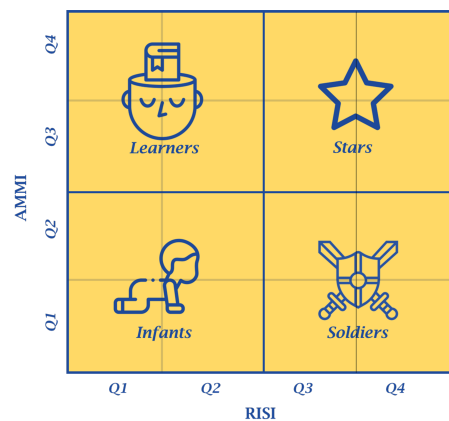


Figure 7.2: Visualisation model - RISI and AMMI.

Table D.1 in Appendix D.1 outlines all utilities' classifications in 2020. A summary of the classification is shown in Table 7.4 and the distribution of the 223 utilities is presented in Figure 7.3.

Table 7.4: Summary of utilities' categories in asset management performance.

Class	Count	%
Infant	71	31.8%
Learner	41	18.4%
Soldier	41	18.4%
Star	70	34.4%

A correlation test was conducted to verify if improved performance on the AMMI dimension is associated with better performance on the RISI dimension. The results for Pearson correlation show that even though the correlation is significant ($p\text{-value}=0$), the correlation coefficient (ρ) is only 0.325, indicating that the correlation is not strong between the two CIs. These results suggest that the maturity in asset management systems is not necessarily associated with good operational performance in the short term. As previously discussed, it takes time for management efforts to generate operational results.

It is possible to examine the results obtained by some utilities and compare them with past data collected from the literature to illustrate the potential impact of the conversion of managerial actions in asset management into operational results. A group of 19 water retailers simultaneously started to implement asset management practices in 2012-2013 as described by Leitão et al. (2016). At the end of this collaborative project, each utility issued strategic and tactical plans aiming to develop asset management practices. These plans in most cases were effectively implemented. One of those utilities, *SMAS de Almada*, was the only utility in Portugal operating exclusively in the retail market to hold the international certification in asset management, ISO 55001. The results from the computation of RISI and AMMI in 2020 for those 19 utilities are encouraging, as 14 of them have achieved the status of Star. Three of the remaining five utilities had been merged

into other systems, making their results incomparable. This trend is an indication of the positive operational results that can be achieved with the implementation of managerial practices.

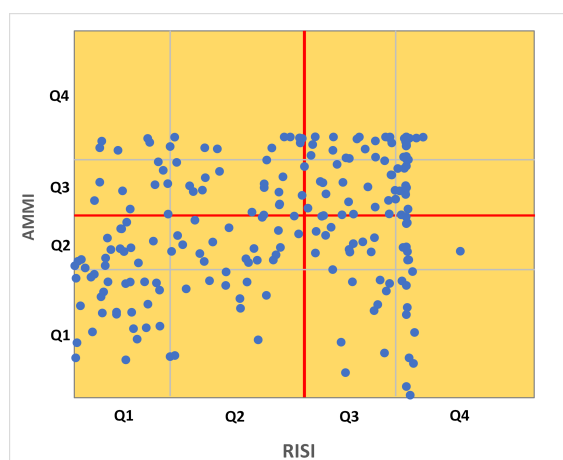


Figure 7.3: Results for RISI and AMMI in 2020
Conditional Approach - All Retail Utilities.

The ten best performers and the ten worst performers in both dimensions are presented in Table 7.5. In the case of AMMI, 11 top-performance utilities are presented because the value of AMMI for the 10th and 11th utility is the same. Their position in the 2x2 Matrix is also shown in Figure 7.4. DMU B45 is identified in black colour in Figure 7.4 because it is classified both as *Bottom 10 RISI* and as *Bottom 10 AMMI*. DMUs B115, B123 and B165 also identified in black colour because they are classified both as *Top 10 RISI* and as *Bottom 10 AMMI*.

Table 7.5: Top 10 and bottom 10 performers in each composite indicator.

RISI Top 10 Performers		RISI Bottom 10 Performers		AMMI Top 10 Performers		AMMI Bottom 10 Performers	
Code	Utility	Code	Utility	Code	Utility	Code	Utility
B163	CM de Sousel	B68	CM de Castelo de Paiva	B44	CM de Alfândega da Fé	B133	CM de Penedono
B168	CM de Vale de Cambra	B120	CM de Moura	B4	Águas da Figueira	B90	CM de Gouveia
B119	CM de Mora	B101	CM de Manteigas	B13	Águas de Gondomar	B57	CM de Arronches
B164	CM de Tábua	B70	CM de Castro Daire	B61	CM de Barreiro	B115	CM de Mondim de Basto
B123	CM de Nisa	B116	CM de Monforte	B66	CM de Bragança	B45	CM de Alijó
B60	CM de Barrancos	B109	CM de Miranda do Douro	B191	Indagua Fafe	B112	CM de Moimenta da Beira
B165	CM de Tabuaço	B179	CM de Vila Nova de Foz Coa	B192	Indagua Feira	B123	CM de Nisa
B63	CM de Bombarral	B110	CM de Mirandela	B193	Indagua Matosinhos	B117	CM de Montalegre
B115	CM de Mondim de Basto	B45	CM de Alijó	B195	Indagua Santo Tirso/Trofa	B98	CM de Lousada
B75	CM de Condeixa-a-Nova	B180	CM de Vila Pouca de Aguiar	B196	Indagua Vila do Conde	B165	CM de Tabuaço
				B201	INOVA		

A closer look at the AMMI outcomes from Table 7.5 reveals that the majority of best performers are managed by concession or delegation (8 utilities), located in urban or semi-urban areas (8 utilities) and are large (9 utilities). However, all of the worst performers are small and managed directly by the municipalities, most of which are located in rural areas (9 utilities). In the case of RISI, no patterns can be observed between the top and bottom performers and the context in which they operate. The trends observed in AMMI results are analysed in more detail using the CI conditional techniques in subsection 6.6.2.

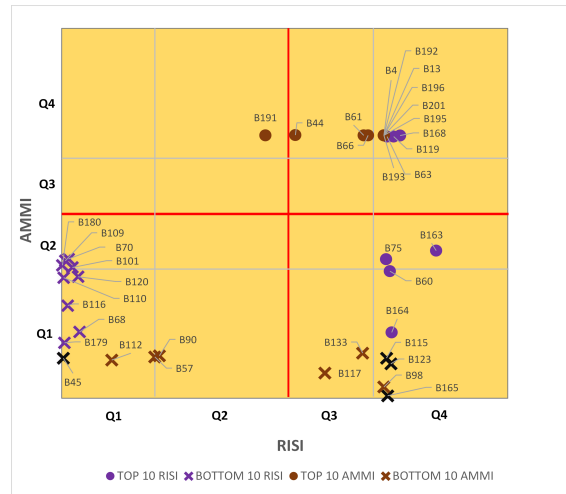


Figure 7.4: Top 10 performers and bottom 10 performers in both dimensions.

7.5.2 Identification of peers and targets

This subsection addresses the designation of utility peers for best-practice identification and selecting the most suitable benchmarking targets for individual utilities.

The targets for the desirable metrics assigned for each utility are obtained from the expressions 7.3 present in Models 7.1 and 7.2. The targets for the undesirable metrics in Model 7.2 are obtained from expression 7.4. These targets represent the projection of the performance metrics toward the efficient best-practice frontier, meaning that if the utility under evaluation can leverage its performance to reach those objectives, it will reach the benchmarking level compared to the other utilities. After the BoD models are solved, using the robust conditional approach, the descriptive statistics for the targets in RISI and AMMI are presented in Table 7.6.

From the results in Table 7.6, one can notice that the average target values do not reach the goals established by ERSAR, meaning that in several cases utilities may achieve levels comparable to their peers without complying with the regulator's objectives. Given the poor performance of the retail operators in these metrics, this result indicates that a revision of ERSAR policy in setting up the goals for asset management targets may be necessary.

Table 7.6: Descriptive statistics for the composite indicators' targets.

CI	Target	ERSAR's goals	Average Performance	N	Robust Cond. DEA/BoD Targets			
					Average	St Dev	Min	Max
RISI	TG_AA09b - Pipeline Rehabilitation (%/year)	≥ 1	0.58	223	0.66	0.91	0.01	5.40
	TG_AA10b - Occurrence of Pipeline Failure (n^o / 100 km.year)	≤ 30	53.12	223	31.82	41.22	0.01	350.00
	TG_AA12b - Actual Water Losses (l/branch.day)	≤ 100	173.74	223	111.63	121.54	2.00	706.30
	TG_AA13b - Energy Efficiency in Pumping Stations (kWh/m^3 .100m)	≤ 0.4	1.71	223	1.00	0.78	0.35	3.24
AMMI	TG_PAA31b - Infrastructure Knowledge Index (Score 0-200)	200	132.2	223	184.70	17.55	71.67	200.0
	TG_PAA32b - Infrastructure Asset Management Index (Score 0-200)	200	40.17	223	43.91	72.16	0.01	200.0

Figures 7.5 and 7.6 display the distribution of the desirable and undesirable metrics' targets,

respectively, alongside the distribution of the actual metrics (observed performance). The black squares in the box plots of Figures 7.5 and 7.6 indicate the averages and the red triangle is the goal determined by ERSAR. Looking at the box plots and the values of standard deviations in Table 7.6, it is noticeable that the variation among the targets is considerable, reinforcing the sector's heterogeneity regarding asset management practices.

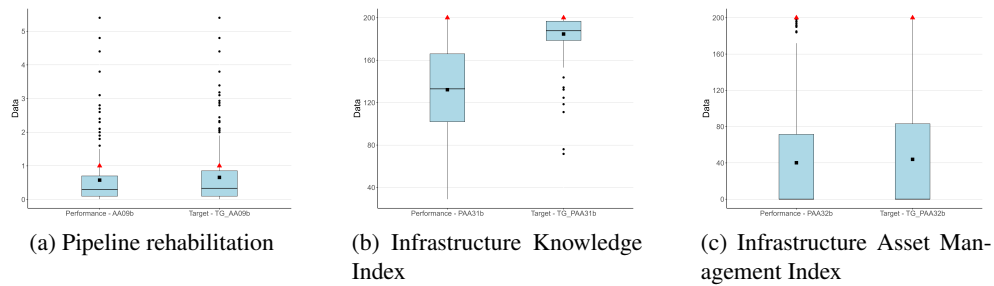


Figure 7.5: Comparison between the distributions of actual performances and targets for the desirable metrics

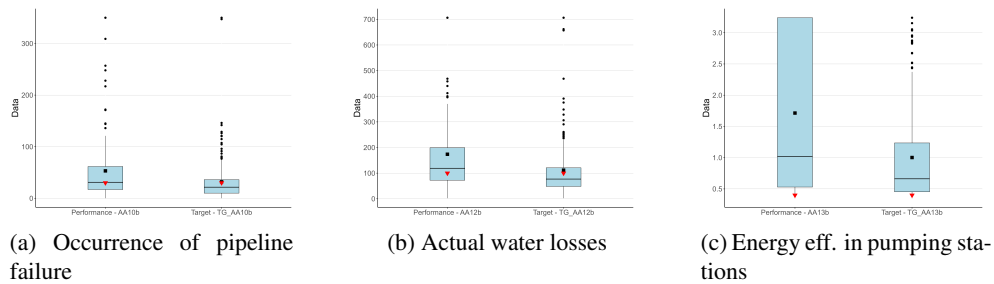


Figure 7.6: Comparison between the distributions of actual performances and targets for the undesirable metrics

This heterogeneity is also seen when the results are analysed in each category assigned in the research (Table 7.7). Even for the Stars, considered the top-performing category, it is noticeable that given their current performance, the goals set by ERSAR look unrealistic in many cases.

Table 7.7: Average metrics and average targets in each category.

Class	Number of Units	CI		Performance and Target for each metric											
		RISI	AMMI	AA09b		AA10b		AA12b		AA13b		PAA31b		PAA32b	
				Average Performance	Average Target	Average Performance	Average Target	Average Performance	Average Target	Average Performance	Average Target	Average Performance	Average Target	Average Performance	Average Target
INFANT	71	0.600	0.539	0.27	0.40	77.61	29.15	210.82	77.20	2.63	1.04	99.32	185.41	4.37	7.97
LEARNER	41	0.639	0.883	0.37	0.51	60.07	32.32	179.06	91.44	2.05	1.07	154.61	175.32	50.88	54.22
SOLDIER	41	0.961	0.530	1.08	1.11	36.44	34.61	227.90	217.77	1.42	1.34	99.98	188.40	4.08	6.18
STAR	70	0.930	0.918	0.71	0.74	33.99	32.59	101.28	96.23	0.76	0.72	171.29	187.30	91.35	96.43

The peers of the utilities are identified as the ones that present the intensity variable λ_j different from zero as an output of the BoD models. The peer set for a given DMU represents its closest anchor on the best-practice frontier, meaning a potentially suitable choice to guide improvements.

In robust and robust conditional approaches, this peer set is more extensive due to the high number of efficient frontiers ($B = 2000$ in this study). The average of λ_j for the sub-sample of B interactions in which the peer was actually selected to compose the sub-sample gives the relevance of the peers.

Following Lavigne et al. (2019), we built an intensity matrix for each CI presenting the average values of λ_j that identify the peers for the robust conditional case. The intensity matrix is a n by n matrix (223×223 in this study), where each row represents a vector of intensities for the evaluated DMUs. The vectors of intensities include the average values of λ_j for each peer identified. One part of the intensity matrix generated in the computation of RISI is displayed in Table 7.8 to illustrate this process. In Table 7.8, it is possible to notice that all utilities in this part of the intensity matrix except B7 and B8 are peers of themselves, meaning that they were identified as efficient in some or all B sub-samples. The utility *B4 - Águas da Figueira* presents a λ_j equal to 1 when compared to itself, which means that it was the only utility included in the efficient frontier in all the B computations performed for its robust conditional BoD assessment. A different situation is noticed for the utility *B7 - Águas de Alenquer*. In this case, *B4 - Águas da Figueira* is found as being a relevant peer for *B7* with λ_j equal to 0.87. The complete intensity matrices are too large to be displayed in the text, but are available upon request to the authors.

Table 7.8: Partial intensity matrix for RISI:
Average λ_j values in the robust conditional approach.

utility	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10
B1 - AGERE	0.80	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
B2 - Águas da Azambuja	0.00	0.06	0.00	0.00	0.00	0.16	0.00	0.00	0.00	0.00
B3 - Águas da Covilhã	0.00	0.00	0.14	0.00	0.02	0.01	0.00	0.00	0.00	0.00
B4 - Águas da Figueira	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00
B5 - Águas da Região de Aveiro	0.00	0.00	0.00	0.17	0.20	0.00	0.00	0.00	0.00	0.00
B6 - Águas da Teja	0.00	0.00	0.00	0.00	0.00	0.99	0.00	0.00	0.00	0.00
B7 - Águas de Alenquer	0.00	0.00	0.00	0.87	0.00	0.00	0.00	0.00	0.00	0.00
B8 - Águas de Barcelos	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
B9 - Águas de Carrazeda	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.93	0.00
B10 - Águas de Cascais	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.07

In the DEA/BoD conditional approach, the selection of samples is not random; utilities that are more alike, and operating in similar environments, have a higher probability of being included in the B sub-samples considered. Therefore, as highlighted by Lavigne et al. (2019), higher values of λ_j indicate that the peer is more relevant because it is comparable in performance and operating environment.

Table 7.9 illustrates the results of the benchmarking assessment using one utility, *SM de Alcobaça - B206*, as an example, employing the robust conditional BoD approach. The table displays the value of each metric alongside the computed targets and ERSAR's goals. *SM de Alcobaça* is classified as Infant, and the calculated targets for most of the metrics are generally realistic and do not reach ERSAR's expectations. For the only two metrics for which this utility's performance is acceptable according to ERSAR's goals, pipeline failures and water losses, the assigned targets are more challenging than the ones set by the regulator. In that sense, this example reveals the BoD technique's ability to provide more suitable targets for each particular DMU.

Table 7.9: Example of target and peer determination:
DMU B206 - utility SM de Alcobaça.

CI	Metric component of CI	Unit	ERSAR's Goals	Actual Performance	DEA/BoD Targets	Peer Performance
RISI	AA09b - Pipeline Rehabilitation	%/year	≥ 1	0.5	0.6	0.4 (B100); 0.6 (B66); 2.1 (B201).
	AA10b - Occurrence of Pipeline Failure	no./(100km.year)	≤ 30	27	19	19 (B100); 20 (B66); 7 (B201).
	AA12b - Actual Water Losses	l/(branch.day)	≤ 100	71	50	6 (B100); 35 (B66); 108 (B201).
	AA13b - Energy Effic. in Pumping Stations	kWh/(m ³ .100m)	≤ 0.4	0.86	0.61	0.95 (B100); 0.47 (B66); 0.35 (B201).
AMMI	PAA31b - Infrastructure Knowledge Index	score	200	85	169	147 (B28); 186 (B66); 190 (B201).
	PAA32b - Infrastructure Asset Manag. Index	score	200	80	159	184 (B28); 200 (B66); 200 (B201).

In the calculation for RISI, 64 peers were identified for *SM de Alcobaça - B206*, while in AMMI model, 39 peers were determined. The three most relevant peers of *SM de Alcobaça* presenting the highest values of λ_j , according to the performance in RISI are *CM de Mangualde - B100* ($\lambda_{100} = 0.21$), *CM de Bragança - B66* ($\lambda_{66} = 0.18$) and *INOVA - B201* ($\lambda_{201} = 0.11$). Regarding AMMI, the three most relevant peers are *INOVA - B201* ($\lambda_{201} = 0.39$), *CM de Bragança - B66* ($\lambda_{66} = 0.16$) and *Águas do Planalto - B28* ($\lambda_{28} = 0.10$). The performance metrics of the peers of *SM de Alcobaça* are presented in Table 7.9 as well. *SM de Alcobaça* should look at their performance and learn from their practices. This exercise is facilitated because they share similar environments as the peer selection generated from the BoD conditional approach.

The entire list of targets and peers is available upon request from the authors.

7.5.3 Role of context on the utilities' performance

This subsection presents and discusses the role of contextual factors on the utilities' performance in asset management.

As explained in subsection 6.4.3, the partial plots with bias-corrected bootstrapped non-parametric confidence intervals of the score ratios (between the robust CI and conditional CI) can be used to assess the relationship between the context and the utilities' performance. The partial plots are obtained using the *np* package in R (Hayfield and Racine, 2008).

Considering the variable Management System (PAA002b), partial plots with confidence intervals are shown in Figure 7.7.

Regarding RISI, no differences are noticed for the different management systems, as shown in Figure 7.7a. Regarding AMMI, the partial plots in Figure 7.7b reveal that the performance of the utilities directly managed by the municipalities is significantly different from the ones managed by concession and delegation. Specifically, the direct management system displays score ratios significantly lower and an unfavourable role on the utilities' AMMI performance. A direct management system implies that the water utility is managed and controlled exclusively by the public sector (municipalities). The other two management systems assume the responsibility of a

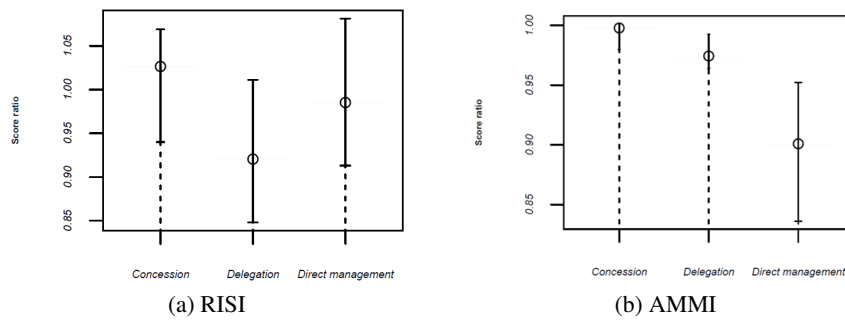


Figure 7.7: Effect of exogenous variable - management system.

designated utility for the services, either through a concession contract or a delegation from the public sector. From the results in Figure 7.7b, concession and delegation models have been more successful in implementing structured practices to manage their infrastructures. The concession and delegation utilities often specialise in the water supply sector and may present more proficient administration. The fact that those utilities present higher maturity in management systems can leverage their operational results in the future.

The effect of the typology of intervention area in asset management performance is displayed in Figure 7.8.

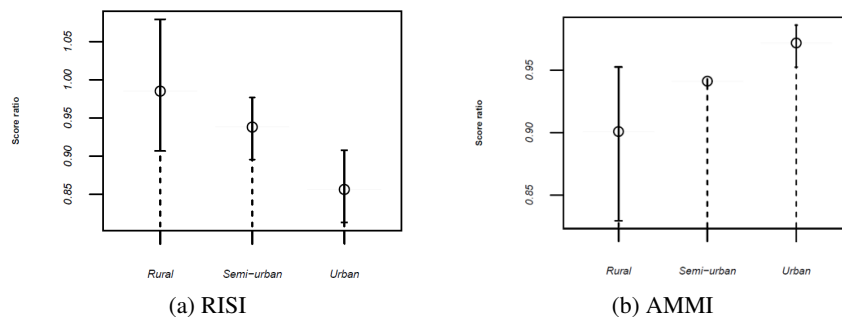


Figure 7.8: Effect of exogenous variable - typology of intervention area.

Regarding RISI, the urban environment is less favourable for operational results, as the graph in Figure 7.8a reveals. The younger infrastructure in Portugal's rural and semi-urban areas may be why urban regions have inferior operational performance. Several extension projects have been carried out in Portugal to expand pipeline networks into rural areas in recent decades. More recent water systems are more likely to be free of leakages or failures, which comprise the RISI metrics.

On the other hand, regarding AMMI, urban settings are more favourable to maturity in management systems, as indicated by the AMMI score ratio in Figure 7.8b. Better knowledge about their assets (such as accurate engineering drawings and records) may explain the better performance in management systems by urban utilities. Notice that the *Infrastructure knowledge index* is one of the components of AMMI.

Regarding the geographic location, Figure 7.9 displays the partial plots for both indicators' performance scores. Results from RISI (Figure 7.9a) and AMMI (Figure 7.9b) show that the geographic regions present similar performance in both dimensions of asset management performance measurement.

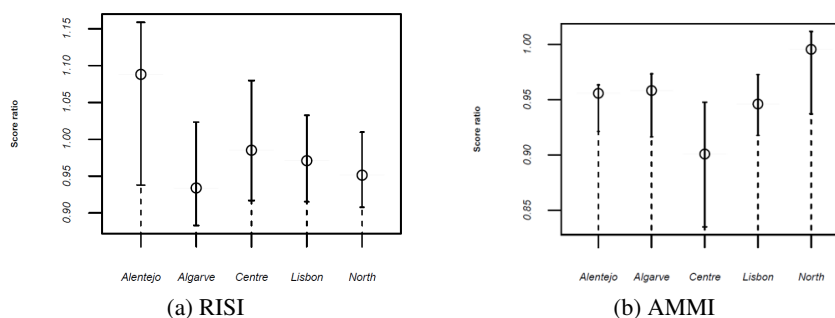


Figure 7.9: Effect of exogenous variable - geographic location

Concerning the volume of activity, the partial plots displayed in Figure 7.10 confirm that the volume of activity makes no statistically significant difference in the performance of both RISI and AMMI.

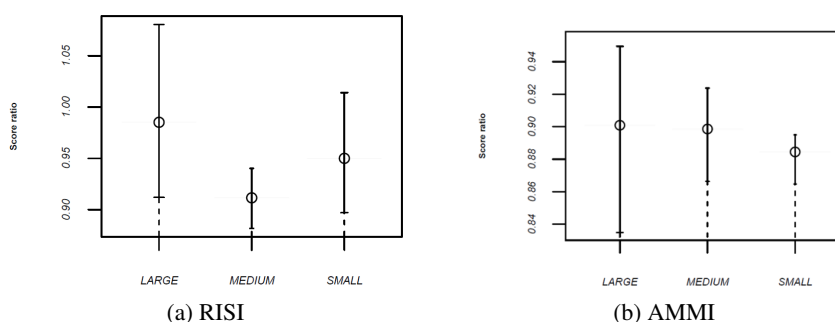


Figure 7.10: Effect of exogenous variable - volume of activity.

7.6 Conclusion

This research contributes to the literature by providing a novel method to identify peers and targets for benchmarking asset management practices in the retail water sector. The benchmarking exercise is carried out using the Portuguese water sector. This unique market is fragmented, displaying hundreds of operators and, is heterogeneous in many facets, such as governance, utility size and service scope. The country's regulatory authority policies actively focus on benchmarking, making this topic relevant. Rather than increasing investments in new assets, the national strategic policy for the industry encourages strengthening current infrastructure management (Frade et al., 2015).

Moreover, the current state of infrastructure preservation is inadequate, making this subject even more critical. The study provides new and adaptable tools for the regulators and utilities

to strengthen sunshine regulation practices. Official metrics issued by the regulatory authority (ERSAR) are employed to construct two Composite Indicators (CIs) reflecting the managerial practices and operational performance of asset management in 223 retail operators. Benefit-of-the-Doubt (BoD) directional distance models enable the computation of the indicators. They are employed to identify the most suitable peers and targets for the benchmarking exercise, representing this study's innovative contribution. A visualisation model for the combined assessment of the two CIs is also provided.

To facilitate statistical inference and investigate the relationship between contextual elements and utility performance, robust and conditional techniques are utilised in addition to the deterministic strategy for building CIs. The most recent models of concession or delegation favour a better performance in managerial practices but do not influence the operational results. The operation in urban areas is favourable for managerial practices but unfavourable for operational results. The performance for tangible results and management features is not sensitive to the volume of water supplied and the geographical location in mainland Portugal.

The targets generated are specific for each operator and reflect the most suitable way to pursue and conduct improvements. The fact that those targets, in most cases, fall short of ERSAR's ideals means that the utilities may need to follow specific and more realistic pathways for their performance. In that sense, the regulatory authority can take advantage of the procedure detailed in this study, setting individual and feasible targets for the sector's operators. By identifying a group of peers for benchmarking asset management practices, the study offers guidance on where to look for recommendations in this highly fragmented and diverse scenario of retail water businesses. The methodology outlined in this study has the potential to be replicated in other developed countries facing similar challenges related to the maintenance and renewal of water supply and sanitation infrastructures, as long as the necessary data is available.

The main limitations of the study rely on the data set available. Even though the data are reliable and provided by an official source, the information gathered needs to be enlarged in several aspects, such as investment details and preservation of vertical assets, such as storage tanks. The results of studies like this can reinforce the practical importance of this information and stimulate the regulatory authority and the operators to expand the collected data set. Furthermore, the study did not involve stakeholders such as regulatory authorities, and other relevant groups in the benchmarking exercise. Including these groups might have provided valuable insights from different perspectives, and incorporating their preferences into the models could have added value to the research and enhanced its practical applicability. Future research can look at the progression of the asset management practices over time, determine each utility's strengths and weaknesses, and explore other perspectives of ERSAR's metrics, such as environmental issues or quality of service.

Further studies could also examine how different ownership and governance structures, such as private sector participation and public-private partnerships, affect asset management practices. Comparing the asset management practices and operational performance of retail water operators in Portugal with those in other countries facing similar challenges could provide valuable insights. Furthermore, examining the effectiveness of different benchmarking methods and tools for im-

proving asset management and investigating the role of regulatory policies on asset management practices in the retail water sector could be worthwhile research avenues to pursue.

Investment project selection in water systems' asset management through optimisation

This chapter aims to present a new method for selecting infrastructure investment projects in the field of asset management. A significant challenge in asset management is the selection of investment projects for infrastructures, which often relies on subjective judgement and lacks structured decision support methods. This challenge is particularly complex in water systems due to the diverse and heterogeneous nature of the components requiring investment. While the Infrastructure Value Index (IVI) is widely used to characterise assets and support investment decisions in the water sector, its application in optimisation models for generating efficient project portfolios remains unexplored. To address this research gap, this study introduces optimisation models for generating investment portfolio plans in water systems' asset management. The proposed approach includes two mixed-integer linear programming (MILP) models that determine optimal solutions and an evolutionary algorithm that offers sub-optimal alternative investment selection plans to provide decision-makers with additional choices for balancing optimal outcomes. The primary contribution of this research is the combined utilisation of MILP and evolutionary algorithms, integrating the IVI into the decision-making process. These tools provide decision-makers with structured methods for defining investment plans and minimising the subjective elements typically associated with such processes. To illustrate the effectiveness of the models, a case study is presented involving a pumping station of a Portuguese water company. The results demonstrate the practical application and benefits of the proposed approach in optimising investment decisions. This research contributes to advancing asset management practices by integrating quantitative optimisation techniques and leveraging the IVI, thereby enhancing the objectivity and efficiency of investment planning in water systems' asset management.

8.1 Introduction

The selection of efficient investment project portfolios is paramount for businesses heavily relying on infrastructure. However, due to the inherent complexity of this task, subjective decision processes often prevail over structured methods. This problem has been recently addressed in the field of asset management.

Infrastructure networks such as roads, power systems, and water systems are crucial for assuring the development of modern economies. An integrated approach is required to operate and

renew those multi-asset systems, which is the focus of the asset management research field. Asset management adopts a holistic concept to asset business problems by covering strategy, safety, environment, cost, risk and life cycle. According to ISO 55000, an organisation can translate its objectives into asset-related activities, plans and decisions to “realise value from assets” (ISO, 2014a). This standard emphasises the relevance of investment decisions among the main strengths of asset management strategies. Identifying the most effective way to invest the available budget represents a critical task for managers, motivating the development of decision tools to guide those choices. Furthermore, the standard emphasises that achieving value requires a balance of costs, risks, and performance benefits, implying that asset management practices entail “trade-offs” that can be evaluated using decision support methods.

Water supply infrastructures are vital systems for human societies. These systems consist of various interconnected components like pipes, pumping stations, treatment plants, and reservoirs, and the reliability of each component can have varying effects on the overall system. Additionally, maintaining the reliability and sustainability of these systems often requires substantial and frequent capital expenditures. As a result, selecting the most appropriate project portfolio is crucial for the water sector.

This work proposes to develop mathematical programming models for capital expenditure project selection in multi-asset systems. A case study based on data from a real-world water supply company is discussed. The Infrastructure Value Index (IVI), an indicator developed in the Portuguese water sector, which is obtained as the ratio between an infrastructure’s current value and its replacement cost, is employed in the models’ formulation.

The IVI, proposed by Alegre (2008), has gained global recognition as a valuable tool for characterising water service infrastructure (Alegre and Covas, 2010; Ramos-Salgado et al., 2022; Cabrera Rochera et al., 2019). The IVI has gained widespread utilisation globally and is increasingly acknowledged as a standard indicator in the water sector, which may be attributed to its simple and intuitive concept. Thus, a growing objective in the water sector is to maintain water infrastructures at the desired IVI level, making it a natural choice for integration into an optimisation approach. Surprisingly, this potential has remained unexplored in the literature, serving as a strong motivation for this research.

Two mixed-integer linear programming models are constructed to generate optimal project portfolios: one aims to improve infrastructure conditions, and the other to reduce capital requirements. The first model aims to maximise the IVI by effectively utilising the available budget to execute projects, while the second model aims to minimise the required investments while maintaining the IVI at a pre-defined level. Additionally, sub-optimal solutions are offered through evolutionary algorithms enhancing decision-making flexibility and striking a balance between the two optimal approaches.

The novelty of this research lies in integrating the IVI into an optimisation framework, a groundbreaking approach not yet explored for selecting an efficient portfolio of investment projects in asset management. This study makes a substantial and innovative contribution to the field by incorporating the IVI into optimisation tools. The methods presented in this study offer several

advantages: they enable the allocation of limited capital towards the most critical needs, provide flexibility in selecting the optimal solution, and are straightforward to implement and communicate. As a result, these methods support consistent prioritisation decisions, underscoring the relevance and practicality of this research.

This chapter unfolds as follows. A brief literature review is presented in Section 8.2. The proposed methodology is described in Section 8.3. The case study is introduced in Section 8.4. The results are discussed in Section 8.5, and the conclusions and opportunities for further works are presented in Section 8.6.

8.2 Literature review

The literature review covers the decision models utilised for project selection in asset management (subsection 8.2.1), and their applications to the water sector (subsection 8.2.2).

8.2.1 Decision models for project selection in asset management

Project portfolios are collections of projects put together for an organisation. Most companies define a budget for capital expenditure (CapEx) projects once a year, and there are usually more potential projects to be implemented than the available capital allows. Those projects compete for scarce resources, such as people, time and capital, so an evaluation process to define a portfolio of CapEx projects is usually needed. The portfolio is picked from a pool of potential project candidates without exceeding the company's resources in accordance with its restriction and organisational requirements (Urli and Terrien, 2010).

Historically, methods for portfolio selection have emerged in the field of operations research. These studies have their origins in capital budgeting, financial portfolio management, and project scoring techniques, and they date back to the 1950s (Liesiö et al., 2021). Project assessments are traditionally performed by applying a discounted cash flow analysis, which involves measures like payback, internal rate of return and net present value (NPV). Nevertheless, according to Yeo and Qiu (2003), those approaches do not reflect the dynamic reality of businesses. Finance and management students learn that the NPV should guide the selection of projects. In practice, however, the NPV analysis represents a modest approach in a decision-making process that includes several variables. The NPV model does not account for the complex activity of selecting projects (Saiz et al., 2022). Besides that, all ordinary economic methods require estimating costs and financial results or profits for the project under consideration. The assessment of project costs may be an arduous and time-consuming task, especially in the early phases of the project, but the profit appraisals can be even more challenging. The problem is that infrastructure asset projects indirectly support several efforts to produce profits, but they seldom generate direct revenues for a business. Therefore, the estimation of project costs may be quantifiable, while the expected cash return is often unpredictable (Gurgur and Morley, 2008). In general, more structured decision models for investment selection can better support the organisation's strategy while considering local objectives, benefits and restrictions (Koppinen and Rosqvist, 2010).

Analytic accuracy, traceability, transparency, and resolution of conflicts between stakeholders or decision-makers are the main advantages of using decision models that have been increasingly applied for asset management problems. Kabir et al. (2014) published a literature review focused on the application of multicriteria decision-making (MCDM) techniques for asset management that revealed considerable growth in the number of papers recently published in this area.

As assets deteriorate with age, the demand for maintenance normally grows, and a decision must be made whether to continue with regular maintenance or to conduct a renewal project. Dias et al. (2021) argue that the degradation of assets is stochastic, which makes intervention planning a challenging task in a multi-asset scenario. Therefore, researchers often adopt the assumption of continuous asset deterioration to simplify their methods, making them more suitable for high-level strategies. Cabral et al. (2019) highlight the knowledge gap regarding asset degradation, which leads to a common practice of using a simplified linear depreciation approach. These authors stress that the clarity of linear depreciation is preferable to seem sophisticated but unreliable methods, as sufficient data for non-linear depreciation is often scarce.

Petchrompo and Parlikad (2019) identified project selection as one of the most common applications of decision methods in asset management, together with a maintenance policy decision, intervention schedule, spare parts management, asset prioritisation, and resource allocation. Regarding project selection, those authors discuss that in the case of multi-asset systems, most decisions tend to be based on subjective judgement due to the complex characterisation of the many heterogeneous assets comprising the system. Defining objectives that yield benefits for the organisation and its stakeholders is usually challenging for those arrangements, where several types of assets may require different metrics. One approach to addressing this issue is to establish a standard metric that can be assigned to every asset in the portfolio. Some works utilised a condition assessment scale as the common metric for assets (Farran and Zayed, 2015; Orcesi et al., 2016). Fwa and Farhan (2012) developed a two-stage model in which different asset classes are evaluated using their specific index in the first stage, and all the metrics are combined in the second stage. Gharaibeh et al. (1999, 2006) proposed an efficiency index to allocate capital performing trade-off assessments among asset categories in transportation facilities. Falls et al. (2006) proposed the Asset Service Index (ASI) that combines the performance of various kinds of assets. This index applied to civil infrastructures measures deviations from an asset's expected condition due to actions or changes that could impact deterioration. The ASI can be applied to different asset categories, but it depends on developing a specific performance model for each type of asset. A more straightforward approach was proposed by Alegre (2008) in the formulation of the Infrastructure Value Index (IVI), used by the sector of water and wastewater. The IVI formulation is the current value of an infrastructure divided by its replacement cost, and the estimation of those parameters are based on the assessment of assets' replacement costs and service lives, incorporating the forecasts of remaining useful lives. Extending assets' lives by even a small proportion can generate significant savings. The impacts of investment projects on assets' service lives can be incorporated in the IVI prediction and are applied in this work.

Optimisation methods have been often applied as decision-making tools for asset management.

On the literature review prepared by Chen and Bai (2019), 337 articles published between 1975 and 2018 were examined, covering a broad range of optimisation applications to asset management. The authors highlight that optimisation methods have become increasingly popular since the 2000s taking advantage of mathematical analysis, and presenting a high potential to support asset management decision-making problems. Optimisation can handle large sets of asset data with the help of powerful computers, finding solutions for complex problems. Moreover, optimisation can promote the best use of available resources, deal with uncertainties and different management outcomes, examine their trade-offs and involve multiple objectives. The most common optimisation tools employed for infrastructure maintenance, rehabilitation or renewal project selection are linear programming (Abiri-Jahromi et al., 2009; Grivas et al., 1993; Park and Lim, 2021) and heuristic methods as, for instance, genetic algorithms (Juan et al., 2010; Miyamoto et al., 2000; Tack and J. Chou, 2002). Multi-criteria decision aiding tools have been also used for decision tools for asset management (Kiss and Tanczos, 1998; Bana e Costa et al., 2006; Fiorencio et al., 2015) as well as Data Envelopment Analysis (Rogers and Louis, 2007; Tavana et al., 2015)

In general, asset project selection problems can be classified into two types: budget allocation and budget planning. The problem of budget planning minimises the necessary funding over a planning horizon, subject to specific requirements at the asset level. This kind of problem is often solved when the necessary budget for investments in assets is unknown. That is different from the budget allocation problem, that is resolved when the limit of the available capital is known. In this case, the problem is solved to maximise the portfolio efficiency, based on the defined objective, or to minimise costs, subject to some budget constraints (Gao et al., 2012; France-Mensah and O'Brien, 2018). In this work, optimisation models are developed to address both problems.

8.2.2 Applications of decision models for investment project selection in the water sector

Water supply systems are a typical example of a multi-asset network that may need significant capital expenditures to maintain their performance and service quality at the required levels. Investment projects in water systems are justified by expansion needs, adaptation to new demands by consumers or legislation, or obsolescence of materials and technologies, in addition to deterioration caused by ageing infrastructure. Thus, investments in water systems must be continuous, throughout the life cycle of the assets. The deterioration in water system components may cause service interruptions, requiring continuous rehabilitation. One vital aspect of companies in the water sector is the social and legal implications of interrupting services. Moreover, different infrastructure assets are often interconnected, and the interruptions in water systems can cause cascading effects in other assets, such as roads and electrical networks. An appropriate level of reliability must be ensured for those systems, such that interruption and breakage events are avoided as much as possible.

Optimisation models applying genetic and evolutionary algorithms are frequently used in water facilities, such as Dandy and Engelhardt (2001), Wang and Chen (2016), Shin et al. (2016), Zangenehmadar et al. (2020), Dridi et al. (2008) to minimise the cost of repairing or replacing

pipe networks. Ramos-Salgado et al. (2021) also propose a genetic algorithm for optimising pipe replacement works based on their proximity and renewal priorities. Other approaches for prioritising repair and replacement actions utilise multi-criteria decision aid (Carriço et al., 2012) and logistic regression (Rifaai et al., 2022). Those studies address pipe replacement and do not consider infrastructure project selection in multi-asset systems. For a comparison between studies that cover replacement prioritisation methods, see Ramos-Salgado et al. (2022).

The use of performance indicators is common in the field of wastewater and water systems, as seen in works like Santos et al. (2019), Haider et al. (2014), and Matos et al. (2003), which present lists of indicators that address various aspects of these systems. Decision methods using performance indicators have often been used for intervention selection and prioritisation of action plans in water companies. Indicators that express performance regarding water leakages (Cavazzini et al., 2020), sustainability (Han et al., 2015; Lee and Burian, 2020, 2019) and resilience (Liu et al., 2020a,b) have been proposed.

The Infrastructure Value Index (IVI) introduced by Alegre (2008) has been discussed worldwide as a tool to characterise water service infrastructure and address investment planning to overcome risks (Alegre and Covas, 2010). According to Ramos-Salgado et al. (2022), the IVI is the most commonly used water infrastructure indicator in the European scientific literature. Meanwhile, Cabrera Rochera et al. (2019) notes that it is quickly becoming a norm to assess the condition of water infrastructure. The IVI standard calculation is straightforward to understand, determined by finding the ratio between the current value of the infrastructure and the cost of replacing it. The infrastructure's current value is often estimated based on assets' useful lives. An alternative calculation of the IVI was proposed by Alegre et al. (2014) and better detailed by Amaral et al. (2016), determining current values based on the performance of selected service indicators, which overcomes the difficulties associated with obtaining current values through assessment of useful lives

Regarding the use of the IVI for investment planning, Alegre et al. (2014) discuss how this indicator varies over time as a consequence of a given investment plan, using the estimation of an infrastructure's level of service to predict the long-term IVI. New formulations for long-term IVI considering the effect of capital investments were proposed by Vieira et al. (2020a,b) and Costa (2021). The authors discuss the impact of a set of planned projects on the IVI, but the selection of optimum project portfolios is not explored. Recent works have used the IVI to address future investment scenarios in conjunction with other indicators as the Infrastructure Degradation Index (IDI), developed by Cabrera Rochera et al. (2019) and the Asset Sustainability Index (ASI), introduced by Urrea-Mallebrera et al. (2019). Cabral et al. (2019) emphasise the economic valuation of assessing incorporating assets' condition to plan rehabilitation interventions.

The IVI can help prioritise investments as infrastructure projects often aim to extend the life of assets and thus change the IVI value. Moreover, since the IVI formulation only requires the estimation of assets' service lives and replacement costs, it can be applied to a wide range of asset classes in different sectors. The previous studies that use the IVI focus primarily on piping replacement. However, rehabilitation initiatives are carried out in many types of assets, such

as instrumentation systems or electrical boardrooms, that do not necessarily require complete replacement. Investment projects with expenses lower than their replacement costs can be carried out for these assets aiming to extend their service lives.

The IVI is still a topic that needs further exploration, especially regarding the uncertainties regarding its central concepts like the estimation of replacement costs, depreciation curves, and service lives (Cabral et al., 2019). Despite its limitations, IVI, as the primary metric in this work, was favoured due to its widespread recognition in infrastructure management and simplicity in conveying information about asset conditions, making it a valuable tool for managerial decisions.

The novelty of this work relies on the use of optimisation models, including MILP and evolutionary algorithms developed to (i) provide flexibility of alternatives to decision-makers, comprising maximisation of assets' condition, informed by the IVI, minimisation of capital expenditure keeping a particular condition, or intermediate solutions between the optimal extremes; (ii) include several kinds of assets, not being limited to pipe replacements, and (iii) possibility of considering alternatives either for performing renewal projects, partial rehabilitation initiatives, or expansion investments.

The problem addressed in the study concerns the selection of an optimal project portfolio for investments to minimise the subjective nature inherent in such processes. The research objective is to develop a structured decision-support tool based on optimisation methods to offer improved alternatives for decision-makers while maintaining flexibility to adapt to real-world contexts. The primary goal is to provide various viable solutions, allowing decision-makers to select the most appropriate outcome that aligns with their needs. By offering different options, the approach strikes a balance between informed recommendations and the ability to tailor the portfolio to each situation's unique requirements and constraints. By reducing subjectivity and enhancing decision-making effectiveness, this research enhances the overall quality of project portfolio selection in investment processes.

8.3 Methodology

The research methodology we propose consists of three main stages. The first one presents the initial characterisation of the assets analysed based on the definition of their technical condition. This is expressed by the IVI values estimated at the beginning of the planning period, followed by the quantification of the effect of potential investment projects on the IVI. The second stage involves the development of two optimisation models that are designed to answer the main research questions, as follows:

- (i) RQ1 - How can a project plan for investments in assets be determined to maximise the overall IVI of an infrastructure?
- (ii) RQ2 - How can an investment plan be determined to maintain the IVI of an infrastructure within the recommended limits during the whole period, whilst minimising the amount of capital required for investment projects in assets?

RQ1 aims to solve a *budget allocation* problem and RQ2 deals with a *budget planning* problem. The results obtained in the optimisation models enable the analysis of the evolution of the IVI for individual assets, groups of assets and the complete infrastructure, given the alternative scenarios considered. The third stage in the research methodology assesses the trade-offs between the outputs of the two optimisation models using a multi-objective approach.

8.3.1 IVI assessment

The IVI can be obtained by the ratio of the Infrastructure Current Value, ICV, and its replacement cost, IRC. It ranges from 0 to 1, or 0% to 100%, where higher values mean that the infrastructure is new or well preserved since its current value is close to the present acquisition cost of a similar infrastructure. The infrastructure has deteriorated if the IVI is low, as its current value is small compared to its replacement cost.

As stated by Alegre et al. (2014), the IVI of well-maintained infrastructures should be between 40% and 60%. Higher IVI values are found for young infrastructures or older infrastructures recently subjected to expansion or rehabilitation, and lower values result from reduced levels of maintenance or renovation. In that sense, applying capital investments to assets can raise the IVI, and maximising IVI values within the recommended range can be consistently employed in project selection for asset management. On the other hand, if no asset investments are performed, the ICV, and consequently the IVI, decreases over time due to ageing. Thus, deciding where and when to invest to reach acceptable IVI levels represents a relevant management problem. Investments that make the IVI too high should also be avoided, so that priority in the use of resources is directed to more deteriorated infrastructures. Furthermore, if investments are concentrated in very short periods, and assets have the same expected lifetime, they will all have to be replaced in a short time window, preventing a balanced distribution of investments overtime.

Determining the Infrastructure's Current Value (ICV) and Replacement Cost (IRC) is necessary to obtain the IVI, so valuation approaches for both terms should be defined. The ICV and the IRC can be estimated as the sum of all current values and the sum of all replacement costs, respectively, associated with the individual assets that compose the infrastructure or the group of assets under evaluation (Alegre et al., 2014). The replacement costs represent the cost of substituting assets with other ones with the same characteristics. These costs can be assessed by technical evaluation, accounting for currently available technology and, eventually, acquisition costs, for which the effect of inflation can be considered (Alegre and Covas, 2010).

However, estimating the current value of an asset can be challenging since the trivial way to provide value to an existing asset is to consider it as a new one. Alegre and Covas (2010) take into account the annual depreciation, so the product of an asset's remaining useful life, or residual life, multiplied by its annual depreciation gives its current value. Those authors estimate the annual depreciation using an economic method, that deals with the changes in the asset's economic value, the update in its useful life and future resultant cash-flows. In this theoretical approach, the annual depreciation is obtained as the replacement cost of the asset, divided by the total useful life. Therefore, the three key parameters necessary to estimate the IVI for groups of

assets or infrastructures are assets' useful lives, residual lives and replacement costs (Alegre and Covas, 2010; Alegre et al., 2014). If those concepts are combined, the IVI formulation in period t introduced by Alegre (2008) is given by (8.1) .

$$IVI_t = \frac{\sum_{i=1}^N \frac{rl_{it} \times rc_{it}}{ul_i}}{\sum_{i=1}^N rc_{it}} \quad (8.1)$$

where for asset i in period t , rl_{it} is the residual life, ul_i is the useful life, and rc_{it} is the replacement cost. A particular case of expression (8.1) is the IVI for a single asset i , which can be estimated by the ratio between its residual life and useful life, as demonstrated in (8.2).

$$IVI_{it} = \frac{\frac{rl_{it} \times rc_{it}}{ul_i}}{rc_{it}} = \frac{rl_{it}}{ul_i} \quad (8.2)$$

The comparison of expressions (8.1) and (8.2) shows that the IVI for groups of assets or complete infrastructures is a weighted average of single assets' IVI, with the weights corresponding to the assets' replacement costs.

There are different ways to estimate assets' useful lives, residual lives and replacement costs. The standard technical useful lives for each kind of asset in water facilities are suggested by the Portuguese regulatory agency, *ERSAR - Entidade Reguladora dos Serviços de Águas e Resíduos* (Alegre and Covas, 2010). Given the values for an asset's useful life, the most trivial way to obtain its residual life is to subtract the asset's age from its useful life.

However, the residual lives can be impacted by the actual condition of the assets, so an adjusted residual life (rl_{it}^{adj}) must be determined to obtain more accurate estimates of the IVI. Alegre and Covas (2010) present an asset classification according to its preservation condition based on the infrastructure conservation classification from U.S. Environmental Protection Agency. That classification can be used as an input to adjust asset's residual life.

After the asset's adjusted residual life (rl_{it}^{adj}) is determined by examining its conservation and functionality, the useful life (ul_{it}^{adj}) is obtained by adding the asset's age (a), as shown in (8.3).

$$ul_{it}^{adj} = rl_{it}^{adj} + a_{it} \quad (8.3)$$

The IVI at the beginning of the planning period for groups of assets and complete infrastructures can be defined using (8.1) (for $t = 0$), assuming that replacement costs, adjusted residual and adjusted useful lives have been previously estimated.

After determining the IVI for the base year, we need to analyse how the initial value of adjusted residual lives and adjusted useful lives are affected by a certain amount of capital invested in assets during the planning period. That is the foundation for developing the optimisation models to choose the most suitable portfolio of projects.

Note that investment projects can be targeted at a single asset or at several assets. In this research, projects involving several assets will require the subdivision of their impact at the asset

level, and consequently, the data required for the optimisation should be collected for individual assets.

Consider the new parameter Δ_{ip} representing the increment that each project p induces to the remaining life of an asset i . The estimation of this parameter may be difficult in real-world contexts, especially if company data is not detailed at the asset level. The involvement of experienced company staff or expert opinion may be critical for obtaining robust estimates of this parameter.

As assets may benefit from more than one project, consider P_i the total amount of potential projects assigned to a given asset i . In this instance, the estimation of rl_{it}^{adj} should consider the impact in the asset's residual life of carrying out several projects. The adjusted residual life of asset i in the year t , after the projects p are carried out, is given by (8.4). This expression establishes a relationship between the residual life in t and $t - 1$, so it incorporates the decrease in residual life by one year from t to $t - 1$.

$$rl_{it}^{adj} = rl_{i(t-1)}^{adj} - 1 + \sum_{p=1}^{P_i} \Delta_{ip} \quad (8.4)$$

The asset's adjusted useful life, ul_{it}^{adj} , can be expressed as (8.5) by adding the asset's age to its residual life.

$$ul_{it}^{adj} = \underbrace{rl_{i(t-1)}^{adj} - 1 + \sum_{p=1}^{P_i} \Delta_{ip}}_{rl_{it}^{adj}} + \underbrace{a_{i(t-1)} + 1}_{a_{it}} \quad (8.5)$$

Expressions (8.4) and (8.5) need to be adjusted to convey the values of rl_{it}^{adj} and ul_{it}^{adj} in terms of the parameters' initial value. Equations (8.6) and (8.7) express them using the residual life characterisation at the start of the planning horizon, rl_{i0}^{adj} (in $t = 0$). Note that $a_{it} = a_{i0} + t$.

$$rl_{it}^{adj} = rl_{i0}^{adj} - t + \sum_{j=1}^t \sum_{p=1}^{P_i} \Delta_{ip} \quad (8.6)$$

$$ul_{it}^{adj} = rl_{i0}^{adj} + a_{i0} + \sum_{j=1}^t \sum_{p=1}^{P_i} \Delta_{ip} \quad (8.7)$$

The single asset IVI considering the effect of investment projects can be properly formulated using (8.2), (8.6) and (8.7), resulting in expression (8.8).

$$IVI_{it} = \frac{rl_{i0}^{adj} - t + \sum_{j=1}^t \sum_{p=1}^{P_i} \Delta_{ip}}{rl_{i0}^{adj} + a_{i0} + \sum_{j=1}^t \sum_{p=1}^{P_i} \Delta_{ip}} \quad (8.8)$$

Consequently, the IVI for complete infrastructures can be obtained using expression (8.8) for single assets, weighted by their replacement costs, as shown in (8.9). This formula is equivalent to expression (8.1), but it allows the explicit incorporation of the effect of investments projects on

assets executed during the planning horizon.

$$IVI_t = \frac{\sum_{i=1}^N IVI_{it} \times rc_{it}}{\sum_{i=1}^N rc_{it}} \quad (8.9)$$

8.3.2 Optimisation models

The optimisation models will answer the two proposed research questions. The first optimisation model, described in section 8.3.2.1, selects a project portfolio from a pool of potential projects that maximises the overall IVI of the infrastructure, given the budget available for investments in assets in the planning horizon. Hence, the formulation of this method addresses the first research question (RQ1) posed in this study. The objective of the second optimisation model presented in section 8.3.2.2 is to establish an investment project plan that maintains the IVI of the infrastructure within given threshold levels (e.g., between 40% and 60%) during the planning horizon, minimising the amount of capital invested. Therefore, the proposed model developed in section 8.3.2.2 answers Research Question 2 (RQ2).

8.3.2.1 Optimisation model 1: IVI maximisation

Suppose that a company has a list of potential asset investment projects for the following years. The parameters representing the increment in the residual life of asset i (Δ_{ip}) and the amount of capital required for the investment (C_{ip}) characterise the projects that are candidates for selection. It is important to assign project candidates for all assets such that the optimisation can choose the projects that should be executed.

The company goal is to select which projects will be executed each year, considering a limited capital availability. If no investments are performed, the IVI tends to decrease over time, so it would be advantageous to use the available capital to extend assets' residual and useful lives and raise the IVI for the complete infrastructure.

The model's binary decision variables are defined as x_{ipt} to indicate whether an investment project is carried out in year t .

$$x_{ipt} = \begin{cases} 1 & \text{if project } p \text{ is carried out in asset } i \text{ and in year } t; \\ 0 & \text{otherwise.} \end{cases}$$

Therefore, to answer the first research question, we maximise the sum of all the infrastructure's annual IVI values (IVI^{sum}) for an investment planning period of T years starting on year 1. The

objective function can be seen in (8.10).

$$\max IVI^{sum} = \sum_{t=1}^T \frac{\sum_{i=1}^N IVI_{it} \times rc_{i0}}{\sum_{i=1}^N rc_{i0}} \quad (8.10)$$

Note that the IVI of the infrastructure in year t (IVI_t) is a weighted average of the IVI_{it} for the assets i that compose the infrastructure. The weights are the replacement costs of the individual assets (rc_{it}). For optimisation purposes, the weights are assumed as constant along the planning period (i.e., disregarding the effects of project actions on assets). This approach is focused on the acquisition costs, and thus we consider in the objective function the replacement costs in $t = 0$.

Equation (8.11) estimates the IVI of an individual asset i in time period t accounting for the impact of the investment projects selected for execution during the planning horizon. We associate a binary decision variable x_{ipt} to the parameter representing the service life extension of asset i with project p (Δ_{ip}) in the expression (8.8) that estimates the individual assets IVI (IVI_{it}).

$$IVI_{it}(x_{ipt}) = \frac{rl_{i0}^{adj} - t + \sum_{j=1}^t \sum_{p=1}^{P_i} \Delta_{ip} \times x_{ipj}}{rl_{i0}^{adj} + a_{i0} + \sum_{j=1}^t \sum_{p=1}^{P_i} \Delta_{ip} \times x_{ipj}}, \quad (8.11)$$

$$\forall i \in \{1, 2, \dots, N\}, \forall p \in \{1, 2, \dots, P_i\}, \forall t \in \{1, 2, \dots, T\}$$

We highlight that equation (8.11) is not linear. Therefore, proper mathematical transformations are applied to obtain a linear programming formulation and solve it in a standard mathematical programming software. The details of the linearisation process are presented in Appendix E.1. Therefore, constraints (8.11) are replaced by the linear constraints (E.4), (E.5), (E.6), (E.7) and (E.8).

Constraints (8.12) impose that a project p in asset i is executed only once during the planning period.

$$\sum_{t=1}^T x_{ipt} \leq 1, \quad \forall i \in \{1, 2, \dots, N\}, \forall p \in \{1, 2, \dots, P_i\} \quad (8.12)$$

Constraint (8.13) limits the capital applied in projects during the planning horizon to the total available budget at the company (B^{total}). In this expression, C_{ip} represents the amount of capital required for investment project p in asset i .

$$\sum_{t=1}^T \sum_{i=1}^N \sum_{p=1}^{P_i} C_{ip} \times x_{ipt} \leq B^{total} \quad (8.13)$$

Constraints (8.14) and (8.15) assure that capital expenditure is balanced along the planning horizon. These constraints allow for a certain degree of flexibility ($\alpha\%$) around the annual average

of the available capital.

$$\sum_{i=1}^N \sum_{p=1}^{P_i} C_{ip} \times x_{ipt} \leq (1 + \alpha) \times \frac{B^{total}}{T}, \quad \forall t \in \{1, 2, \dots, T\} \quad (8.14)$$

$$\sum_{i=1}^N \sum_{p=1}^{P_i} C_{ip} \times x_{ipt} \geq (1 - \alpha) \times \frac{B^{total}}{T}, \quad \forall t \in \{1, 2, \dots, T\} \quad (8.15)$$

Constraints (8.16) set the upper bound (U) for the infrastructure's IVI for each year of the planning horizon.

$$\frac{\sum_{i=1}^N IVI_{it} \times rc_{i0}}{\sum_{i=1}^N rc_{i0}} \leq U, \quad \forall t \in \{1, 2, \dots, T\} \quad (8.16)$$

Constraints (8.17) and (8.18) ensure that for projects including multiple assets, the sub-projects at asset level must be managed as a unique project, and thus should be scheduled for the same period t . In expressions (8.17) and (8.18), S_k represents each set k of projects p in assets i that are scheduled for the same period t . K is the total amount of project sets. $|S_k|$ is the number of elements in set S_k , and M is a large integer number. The auxiliary decision variables w_{kt} determine the execution of the set of projects.

$$\sum_{i,p \in S_k} x_{ipt} \geq |S_k| - M \times (1 - w_{kt}), \quad \forall k \in \{1, 2, \dots, K\}, \quad t \in \{1, 2, \dots, T\} \quad (8.17)$$

$$\sum_{i,p \in S_k} x_{ipt} \leq M \times w_{kt}, \quad \forall k \in \{1, 2, \dots, K\}, \quad t \in \{1, 2, \dots, T\} \quad (8.18)$$

$$w_{kt} = \begin{cases} 1 & \text{if set of projects } k \text{ is carried out in year } t; \\ 0 & \text{otherwise.} \end{cases}$$

The resulting formulation of the optimisation Model 1 can summarised as follows:

Maximise (8.10)

Subject to (8.11), (8.12), (8.13), (8.14), (8.15), (8.16), (8.17), (8.18)

$$x_{ipt} \in \{0, 1\}, w_{kt} \in \{0, 1\}, \quad \forall i \in \{1, 2, \dots, N\},$$

$$\forall p \in \{1, 2, \dots, P_i\}, \quad \forall t \in \{2, 3, \dots, T\}, \quad \forall k \in \{1, 2, \dots, K\}$$

The values obtained for the decision variables x_{ipt} determine which investment projects shall be selected, and the year they should be executed.

8.3.2.2 Optimisation model 2: Investment minimisation to maintain IVI within target limits

We now develop a new optimisation model to determine the minimum amount of capital that upholds the IVI of the infrastructure at a certain level. As in Optimisation Model 1, we propose a

list of project candidates and estimate parameters Δ_{ip} and C_{ip} for each potential project.

The same binary decision variables x_{ipt} of Optimisation Model 1 are used in Optimisation Model 2.

The objective function, defined in (8.19), minimises the total capital expenditure (C^{total}), which corresponds to the sum of the annual expenditures (C_t^{annual}).

$$\min C^{total} = \sum_{t=1}^T C_t^{annual} \quad (8.19)$$

Constraints (8.20) express C_t^{annual} as the sum of expenditures associated with the projects that are selected in the optimisation for execution in year t .

$$C_t^{annual}(x_{ipt}) = \sum_{i=1}^N \sum_{p=1}^{P_i} C_{ipt} \times x_{ipt}, \quad \forall t \in \{1, 2, \dots, T\} \quad (8.20)$$

Constraints (8.21) set the lower bound (L) for the infrastructure's IVI for all the years in the planning period, according to the target levels

$$\frac{\sum_{i=1}^N IVI_{it} \times rc_{i0}}{\sum_{i=1}^N rc_{i0}} \geq L, \quad \forall t \in \{1, 2, \dots, T\} \quad (8.21)$$

Similarly to the optimisation of Model 1, it can also be added to Model 2 a constraint to prevent the IVI of the infrastructure to raise above the target upper bound (U), as shown in (8.16). Alternatively, the constraints may set the lower bound for a single asset's IVI, instead of the infrastructure IVI, as shown in (8.22).

$$IVI_{it} \geq L, \quad \forall i \in \{1, 2, \dots, N\}, \forall t \in \{1, 2, \dots, T\} \quad (8.22)$$

The remaining constraints of Model 2 are identical to those imposed to Optimisation Model 1: Constraints (8.11) estimate the IVI of individual assets i for period t accounting for the impact of the investment projects selected for execution during the planning horizon. Constraints (8.12) impose that a project is selected only once for the planning period. Constraints (8.17) and (8.18) assure that several projects at the asset level are managed together as a unique project.

The resulting formulation of the optimisation Model 2 can summarised as follows:

$$\begin{aligned} &\text{Minimise} && (8.19) \\ &\text{Subject to} && (8.11), (8.12), (8.16), (8.17), (8.18), (8.20), (8.21), \\ & && x_{ipt} \in \{0, 1\}, w_{kt} \in \{0, 1\}, \forall i \in \{1, 2, \dots, N\}, \\ & && \forall p \in \{1, 2, \dots, P_i\}, \forall t \in \{2, 3, \dots, T\}, \forall k \in \{1, 2, \dots, K\} \end{aligned}$$

8.3.2.3 Analysis of the IVI evolution during the planning period

In both optimisation models, the decision variables x_{ipt} identify the projects that should be carried out during the planning period. Note that these projects are specified at the asset level, and the IVI of all individual assets (IVI_{it}) for the entire planning horizon ($t = 1, \dots, T$) can be calculated using (8.11). With this information, it also is possible to compute the IVI for the complete infrastructure and groups of assets using (8.9).

To obtain a more precise estimation of the IVI, the replacement costs can be adjusted to reflect the changes due to project execution. Alegre and Covas (2010) argue that adjustments in asset replacement costs due to changes in service life expectations are usually subjective and complex.

Although we chose to keep those costs constant for the specification of the optimisation models, as this simplifies computations by avoiding non-linear expressions, we use a more robust specification of replacement costs for the analysis of the evolution of the IVI in a post-optimisation stage. Vieira et al. (2020a,b) and Costa (2021) present formulations for replacement costs that consider different parameters for renewals, replacements and expansions. We used expression (8.23), proposed by Costa (2021), to reflect how the replacement cost of an asset i changes from period t to $t + 1$ after the execution of an investment project.

$$rc_{i(t+1)} = rc_{it} \times (1 - \beta_i) + C_i \quad (8.23)$$

In expression (8.23), β_i corresponds to the percentage of the asset i deactivated by an investment project involving replacements or renewals. If an expansion is performed without any planned deactivation for asset i , β_i is zero; if the asset is totally decommissioned, β_i equals one. The replacement cost of the asset is increased by the amount invested (C_i).

Based on this approach, it is necessary to estimate the parameter β_{ip} for all potential projects to obtain the assets' replacement costs in all years of the planning horizon.

Expression (8.24) represents the adjusted replacement cost of an asset. It is obtained from (8.23), incorporating the decision variables x_{ipt} and allowing the execution of more than one project in an asset.

$$rc_{i(t+1)}^{adj}(x_{ipt}) = rc_{it}^{adj} \times \left(1 - \sum_{p=1}^{P_i} \beta_{ip} \times x_{ip(t+1)}\right) + \sum_{p=1}^{P_i} C_{ip} \times x_{ip(t+1)} \quad (8.24)$$

Having assets' IVI and their adjusted replacement costs available, it is possible to calculate the overall IVI_t of the infrastructure and the IVI of groups of assets in each year of the planning period using (8.9). This procedure was used for the analysis of the results discussed in section 8.5, for both optimisation models.

8.3.3 Multi-objective optimisation

The linear programming models presented in earlier subsections produce optimal project plans that meet two distinct goals: maximise the IVI and minimise the capital expenses. It may be

advantageous to give the decision-maker some alternate choices that represent trade-offs between the optimal solutions.

According to Yang (2014), multi-objective optimisation problems often lack a single optimal solution that simultaneously optimises all the objective functions due to potential conflicts between objectives. In such cases, trade-offs or compromises need to be made, often requiring a reformulation of the problem. One commonly used approach is the weighted sum method, where all the multi-objective functions are combined into a single objective function by assigning weights to each objective. However, this method has drawbacks, as it transforms the original multi-objective problem into a single-objective one, which may not preserve the problem's inherent complexity. The choice of weighting coefficients can be arbitrary, and the resulting solutions depend on these coefficients. Additionally, generating a well-distributed set of points along the Pareto front, which represents the optimal trade-offs between objectives, is typically challenging. Moreover, the weighted sum method is applicable only to convex Pareto fronts, limiting its scope to handling other Pareto front shapes. We chose to use a multi-objective strategy based on evolutionary algorithms to produce other project plans that might represent intermediate solutions to the two original objectives. Evolutionary algorithms are particularly suitable to solve multi-objective optimisation problems because they are less susceptible to the shape or continuity of the Pareto front. Due to the population-based nature of those algorithms, several elements of the non-dominated frontier can be generated in a single run, allowing the selection of the most appropriate solution according to different trade-off measurements. Evolutionary algorithms are widely employed to offer reliable approximate solutions to problems that are inherently challenging to solve efficiently using other techniques, such as mathematical programming. In cases where finding an exact solution for combinatorial problems is computationally demanding, evolutionary algorithms provide a valuable alternative by producing near-optimal solutions that meet the required objectives.

We propose an algorithm based on NSGA-II (Deb et al., 2002) to solve the multi-objective problem. All individuals from t^h population, with $rank_k$ and $distance_k$, comprise a parent population P_g of P size. Selection, crossover, and mutation operators create an offspring population of Q_g of P . A combined population $R_g = P_g \cup Q_g$, of $2P$ size, is sorted according to non-domination rank and crowding distance to choose exactly P population members to the new population P_{g+1} (Deb et al., 2002). The selection is performed through the binary tournament selection algorithm. This algorithm randomly samples two solutions of P_g and compares them according to $rank_k$ and $distance_k$. The best one is chosen for the following procedures. Pairs of selected solutions are randomly formed. These pairs can go through crossover and mutation to create an offspring population Q_g .

8.3.3.1 Coding

An individual k encodes a solution of project assignment. Figure 8.1 exemplifies an individual for a problem with 4 assets, 2 projects for each assets in the planning horizon t_1 to t_5 . The binary matrix represents the project assignment for each year. $z_{ip} = 1$ means that project p is carried out in asset i .

	z_{11}	z_{12}	z_{21}	z_{22}	z_{31}	z_{32}	z_{41}	z_{42}
t_1	0	1	0	0	0	0	0	0
t_2	1	0	0	1	0	1	0	0
t_3	0	0	0	0	0	0	1	0
t_4	0	0	1	0	1	0	0	0
t_5	0	0	0	0	0	0	0	1

Figure 8.1: An example of binary matrix encoding representing each potential solution k in the population.

8.3.3.2 Population Initialisation

The initial population P_g is randomly generated with size $P = 100$ (empirically defined). The individuals are initialised considering the constraints (8.12), (8.17), (8.18) (Section (8.3.2.1)). For constraints (8.12), the project p in asset i is carried out only once during the planning horizon. Constraints (8.17) and (8.18) ensure the sub-projects should be realised in the same year t .

8.3.3.3 Population Evaluation

The individuals from the population are evaluated for each one of the objective values, f_1 (IVI) and f_2 (Total capital expenditure).

$$f_1: \max IVI^{sum} = \sum_{t=1}^T \frac{\sum_{i=1}^N IVI_{it} \times rc_{i0}}{\sum_{i=1}^N rc_{i0}} \quad (8.25)$$

$$f_2: \min C^{total} = \sum_{t=1}^T C_t^{annual}$$

In the case of infeasible solutions, the fitness value also incorporates this information through a penalty costs p_1 and p_2 . Equation (8.25) represents the penalty function regarding the IVI constraints. The first portion is related to each period s that violates constraint (8.21), and the second portion for each period q that violates constraint (8.16).

$$p_1: \min Penalty_{IVI} = \left(L - \frac{\sum_{i=1}^N IVI_{is} \times rc_{i0}}{\sum_{i=1}^N rc_{i0}} \right) + \left(\frac{\sum_{i=1}^N IVI_{iq} \times rc_{i0}}{\sum_{i=1}^N rc_{i0}} - U \right), \quad (8.26)$$

$$\forall s \in S, \forall q \in Q$$

Equation (8.27) represents the penalty function regarding capital expenditure. The first portion is related to each period g that violates constraint (8.14), the second portion for each period h that violates constraint (8.15) and the last one when the amount of capital for all years exceeds the total

available budget at the company.

$$\begin{aligned}
 p_2: \min \text{ Penalty}_C = & \left(\sum_{i=1}^N \sum_{p=1}^{P_i} C_{ip} \times x_{ip(g+1)} - (1 + \alpha) \times \sum_{i=1}^N \sum_{p=1}^{P_i} C_{ip} \times x_{ipg} \right) \times 10 + \\
 & \left((1 - \alpha) \times \sum_{i=1}^N \sum_{p=1}^{P_i} C_{ip} \times x_{iph} - \sum_{i=1}^N \sum_{p=1}^{P_i} C_{ip} \times x_{ip(h+1)} \right) \times 10 + \\
 & \left(\sum_{t=1}^T \sum_{i=1}^N \sum_{p=1}^{P_i} C_{ipt} \times x_{ipt} - B^{total} \right) \times 10, \\
 & \forall g \in G, \forall h \in H
 \end{aligned} \tag{8.27}$$

8.3.3.4 Nondominated Sorting Approach

As defined in Deb et al. (2002), in NSGA-II every individual k is associated with two attributes: $rank_k$ and $distance_k$.

If two solutions have different non-domination levels (different non-dominated frontiers), we choose the solution k with the lower $rank_k$. Otherwise, if two k_1 and k_2 solutions belong to the same frontier ($rank_{k_1} = rank_{k_2}$), then we prefer the solution that is located in a less crowded region (that is, higher $distance_k$) (Rampazzo et al., 2015).

8.3.3.5 Crossover and Mutation

A population of parents is built through binary tournament. Pairs of parents from this population are selected to generate pairs of offspring.

The uniform crossover is applied to each pair of selected solutions, thus generating two offspring. A mask with a uniform distribution is created, each individual has a 50% chance to copy the gene from parent₁ and the other 50% from parent₂. For offspring₁ when mask values is 0, the genes are copied from parent₁, while for offspring₂ the genes are copied from parent₂. When mask values is 1, for offspring₁ the genes are from parent₂ and for offspring₂ from parent₁.

The mutation process complements the crossover, as it allows a larger search space to be explored. For each offspring, two columns of the individual k are randomly selected:

1. if the two projects are carried out in the same year, a new year and a new value $\in \{0, 1\}$ are randomly selected.
2. if the two projects are carried out in different years, the project assignment is swapped.

The offspring population is evaluated by calculating the fitness. The operators of classification and agglomeration are evaluated, considering the merge between both the original and the offspring population. After selecting the next population, a percentage p_e of the worst individuals are replaced with the best individuals. We considered empirically p_e as 0.1, thus, 10% of the population is replaced. The process is repeated with the new population until the total number of generations is attained, this parameter have been empirically defined as 200.

8.4 Case study

A Portuguese water supply company, Águas do Douro e Paiva (AdDP), responsible for water abstraction, treatment, and provision in the region of Porto (Portugal), provided the data to demonstrate the applicability of the proposed technique. The company has already started to apply the IVI in its asset management procedures to test its suitability to monitor the performance of assets in a real-world context.

The data provided includes asset information and the amount of investment planned for the next five years for the Jovim Pumping Station (Jovim PS). This infrastructure includes two different pumping stations (PS 1 and PS 2), each one with four electric pump groups. PS 1 has a lifting capacity of 1,347 l/s and reaches a manometric height of 57.1 m.w.c., and PS 2 has a lifting capacity of 2,718 l/s and 56.2 m.w.c..

Twenty-one assets were identified in Jovim PS. The breakdown of the infrastructure including component group and asset level is presented in Table 8.1. In the same table, the assessments of useful life, replacement cost and asset condition coefficient c , for the year before the planning period (t_0), are available for that infrastructure. The coefficient c is obtained from Table 8.2, used to assess the conservation status of the assets.

Table 8.1: Asset data for Jovim PS Infrastructure in t_0

Asset	Description	Group	Age (years)	State of condition (c)	Theoretical total useful life (years)	Replacement cost (€)
1	Jovim Building	Civil Work	22	1.2	50	645,000.00
2	Jovim Piping	Civil work	22	1.2	40	645,000.00
3	Electrical boardroom in PS 2	Electrical facilities	22	2.1	15	250,000.00
4	Electrical boardroom in PS 1	Electrical facilities	22	1.9	15	250,000.00
5	Transformer substation in PS 1	Electrical facilities	22	1.7	15	224,000.00
6	Transformer substation in PS 2	Electrical facilities	22	1.6	15	280,000.00
7	Generator group in PS 2	Equipment	21	1.5	20	20,000.00
8	Instrumentation, automation, control and measurement	Equipment	9	1.0	15	100,000.00
9	Pumping group 1 in PS 1	Equipment	19	1.4	20	180,000.00
10	Pumping group 2 in PS 1	Equipment	19	1.4	20	180,000.00
11	Pumping group 3 in PS 1	Equipment	19	1.4	20	180,000.00
12	Pumping group 4 in PS 1	Equipment	19	1.4	20	180,000.00
13	Pumping group 1 in PS 2	Equipment	21	1.3	20	285,312.39
14	Pumping group 2 in PS 2	Equipment	21	2.1	20	285,312.39
15	Pumping group 3 in PS 2	Equipment	21	1.3	20	285,312.39
16	Pumping group 4 in PS 2	Equipment	21	2.1	20	285,312.39
17	Ventilation in PS 1	Equipment	22	1.7	15	20,000.00
18	Ventilation in PS 2	Equipment	22	1.3	15	20,000.00
19	Pressure Tank 1	Equipment	9	1.7	40	56,388.62
20	Pressure Tank 2	Equipment	9	1.7	40	56,388.62
21	Pressure Tank 3	Equipment	9	1.6	40	88,917.66

Note: PS = Pumping Station.

Table 8.2: Conservation status classification proposed by U.S. EPA (Alegre, 2008)

State of condition (<i>c</i>)	Description	Required rehabilitation rate
1	In perfect condition	0%
2	It has minor anomalies	5%
3	Presents anomalies that require significant curative maintenance	10-20%
4	Requires renewal	20-40%
5	Practically unusable asset	>50%

The company has defined the assets' adjusted residual lives for t_0 , rl_{i0}^{adj} , considering the empirical expression (8.28) proposed by Costa (2021)

$$rl_{i0}^{adj} = ul_i - \left(\frac{ul_i}{5} \times c \right) \times \left(\frac{a_{i0}}{ul_i} \right)^{\frac{1}{c+1}} \quad (8.28)$$

where a_{i0} is the known age of an asset i in period $t = 0$, and its useful technical life, ul_i , is obtained based on the recommendations of the Portuguese regulatory agency (Alegre and Covas, 2010). After the adjusted residual lives are determined, the adjusted useful lives can be obtained using expression (8.3).

The company plans to invest 665,000€ in asset projects for Jovim PS in the following five years. For this 5-year period, considering the current condition and the residual life of the assets, the company is able to establish a list of possible projects that can be selected for execution. In the case study considered, 42 hypothetical potential projects, or project ideas, were proposed for selection and execution during the period considered. Certainly, after this 5-year period, new investments will have to occur to maintain the IVI at the desired levels and, the method of selecting these new projects can be performed again, taking into account the updated and more accurate condition of the assets. The 42 candidate projects are presented in Table 8.3. The values of parameter β_{ip} reflect the percentage of the original asset's decommissioning after investment project execution. The values for C_{ip} represent the planned budget for each project. The parameter Δ_{ip} represents the potential extension in the asset's useful life generated by each project. The company decided that two sets of projects involving ventilation assets (17 and 18) must be managed as a unique project: P_{17a}/P_{18a} and P_{17b}/P_{18b} .

Table 8.3: Portfolio of hypothetical project candidates

Project (P_{ip})	β_{ip}	Δ_{ip}	C_{ip} (€)	Project (P_{ip})	β_{ip}	Δ_{ip}	C_{ip} (€)
P _{1a}	0.10	6,37	64,500.00	P _{1b}	0.20	12.75	129,000.00
P _{2a}	0.10	5,47	64,500.00	P _{2b}	0.20	10.94	129,000.00
P _{3a}	0.20	5.97	50,000.00	P _{3b}	0.40	11.95	100,000.00
P _{4a}	0.20	6.10	50,000.00	P _{4b}	0.40	12.20	100,000.00
P _{5a}	0.20	6.22	44,800.00	P _{5b}	0.40	12.45	89,600.00
P _{6a}	0.20	6.29	56,000.00	P _{6b}	0.40	12.58	112,000.00
P _{7a}	0.20	6.98	4,000.00	P _{7b}	0.40	13.95	8,000.00
P _{8a}	0.10	2.17	10,000.00	P _{8b}	0.20	4.34	20,000.00
P _{9a}	0.10	3.35	18,000.00	P _{9b}	0.20	6.70	36,000.00
P _{10a}	0.10	3.35	18,000.00	P _{10b}	0.20	6.70	36,000.00
P _{11a}	0.10	3.35	18,000.00	P _{11b}	0.20	6.70	36,000.00
P _{12a}	0.10	3.35	18,000.00	P _{12b}	0.20	6.70	36,000.00
P _{13a}	0.10	3.57	28,531.24	P _{13b}	0.20	7.14	57,062.48
P _{14a}	0.20	6.49	57,062.48	P _{14b}	0.40	12.99	114,124.96
P _{15a}	0.10	3.57	28,531.24	P _{15b}	0.20	7.14	57,062.48
P _{16a}	0.20	6.49	57,062.48	P _{16b}	0.40	12.99	114,124.96
P _{17a}	0.20	6.22	4,000.00	P _{17b}	0.40	12.45	8,000.00
P _{18a}	0.20	6.48	4,000.00	P _{18b}	0.40	12.96	8,000.00
P _{19a}	0.10	4.12	5,638.86	P _{19b}	0.20	8.23	11,277.72
P _{20a}	0.10	4.12	5,638.86	P _{20b}	0.20	8.23	11,277.72
P _{21a}	0.10	4.18	8,891.77	P _{21b}	0.20	8.36	17,783.53

The following rules were applied to estimate the project parameters and test the optimisation models. In future implementations, these parameters should be determined based on the company's knowledge:

- β_{ip} : The proposed set of hypothetical projects for the case study includes two projects for each asset with $\beta_{ip} = 0.10$ and $\beta_{ip} = 0.20$ for the assets presenting an IVI greater than 40.0% in t_0 . For low-IVI assets, being less than 40.0%, that demand higher investments, the candidate projects present $\beta_{ip} = 0.20$ and $\beta_{ip} = 0.40$.
- Δ_{ip} : This parameter is estimated as being proportional to the ratio between the capital invested in the project (C_{ip}) and the asset's replacement cost, as in (8.29). For this estimation, the values already known for t_0 were employed. From expression (8.29), a project capital investment applied to an asset representing, for example, 10.0% of its replacement cost should increase the asset's useful life by 10.0%.

$$\Delta_{ip} = \frac{C_{ip}}{rc_{i0}} \times ul_{i0}^{adj} \quad (8.29)$$

- C_{ip} : The values of the required capital for the projects were estimated as the cost to reestablish the decommissioned parcel of the asset (β_{ip}), or equivalent to a parcel of the asset's replacement cost that had been decommissioned, calculated as $C_{ip} = \beta_{ip} \times rc_{i0}$.

8.5 Results and discussion

The two mixed-integer optimisation models were solved using IBM ILOG CPLEX version 20.1.0.0. The computational time needed to solve Optimisation Model 1 was approximately 57 minutes,

while Optimisation Model 2 was solved within the predefined one-hour time limit, resulting in a gap of 0.38%. The lower (L) and upper bounds (U) for IVI were set to 40% and 60%, respectively, following the recommendations of Alegre et al. (2014). Regarding the parameter α used in constraints (8.14) and (8.15) in Optimisation Model 1, a sensitivity analysis was performed to verify the variation of the objective (IVI^{sum}). The results are shown in Figure 8.2. From the rate $\frac{dy}{dx} = 0.0963$ in the trendline, we see that the incremental gain in the IVI^{sum} (y axis) is minimal when varying α (x axis). With this sensitivity analysis, we see that the model is robust and has minor sensitivity to the value of α . Therefore, α was assumed as 0.5 to allow a certain flexibility in capital expenditures among the years under analysis.

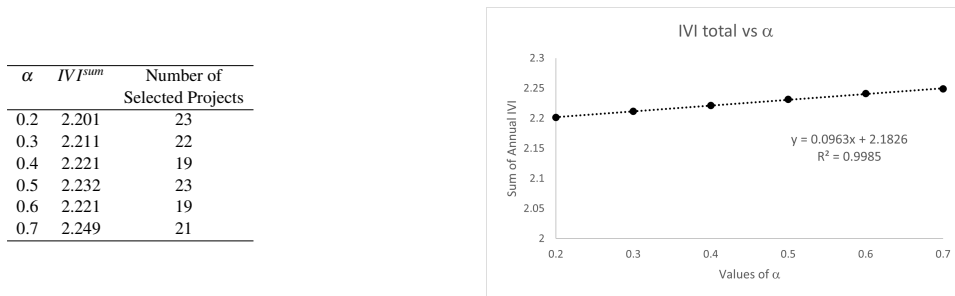


Figure 8.2: Sensitivity analysis for parameter α

The outcomes of Optimisation Models 1 and 2 are identified in this work as Optimal Plans 1 and 2, respectively. Optimisation Model 1 is designed to provide an answer to Research Question 1 (RQ1), while Optimisation Model 2 is formulated to address Research Question 2 (RQ2).

Each one of the plans was designed to reach a different objective. The analysis of models' outcomes is performed using the average IVI of individual assets for the whole planning period, the overall IVI for the infrastructure and the IVI for the three different groups of assets: civil work, equipment and electrical facilities.

A no-investment condition was used for comparison to illustrate the effect on the IVI of postponing or avoiding asset investments. In that situation, the company would not invest any capital in its assets during the period, so the IVI calculation is performed as per the procedure described in subsection 8.3.2.3, but using x_{ipt} equal to 0 in all assets and years.

8.5.1 Determination of IVI at the beginning of the planning project period

Following the methodology described in Subsection 8.3.1, the average IVI for individual assets and IVI for the infrastructure and category groups can be seen in Table 8.4. The detailed results at the beginning of the planning horizon (t_0) are shown in Table E.1 in Appendix E.2.

From those results, the overall IVI for Jovim PS, with a value of 46%, is currently at an acceptable level. However, the IVI values for nine assets (out of 21) are below 40%, including all from the electrical facilities group. This suggests that electrical facilities demand more attention in terms of asset conservation.

Table 8.4: IVI values for Jovim PS infrastructure in year t_0

Single Asset's Average	Infrastructure	Civil work	Equipment	Electrical facilities
42.1%	46.0%	62.6%	44.3%	28.4%

8.5.2 Results of optimisation models

The optimal project plans generated from Optimisation Models 1 and 2 are presented in Table 8.5. The table displays the year of execution for each selected project, considering that, if a project P_{ip} has been selected, the resulting decision variable x_{ipt} equals 1.

Table 8.5: Selected projects for each year of the planning horizon (t_1 to t_5) from Optimisation Models 1 and 2

Asset Group	Optimal Plan 1				Optimal Plan 2			
	Project	Year	Project	Year	Project	Year	Project	Year
Civil work	P _{1a}	-	P _{1b}	-	P _{1a}	-	P _{1b}	-
	P _{2a}	-	P _{2b}	-	P _{2a}	-	P _{2b}	-
Electrical facilities	P _{3a}	t_1	P _{3b}	-	P _{3a}	t_5	P _{3b}	-
	P _{4a}	t_1	P _{4b}	-	P _{4a}	t_1	P _{4b}	-
	P _{5a}	t_1	P _{5b}	-	P _{5a}	t_4	P _{5b}	-
	P _{6a}	t_2	P _{6b}	-	P _{6a}	t_2	P _{6b}	-
Equipment	P _{7a}	t_3	P _{7b}	-	P _{7a}	-	P _{7b}	t_2
	P _{8a}	t_4	P _{8b}	-	P _{8a}	-	P _{8b}	-
	P _{9a}	t_1	P _{9b}	-	P _{9a}	t_1	P _{9b}	-
	P _{10a}	-	P _{10b}	t_3	P _{10a}	t_1	P _{10b}	-
	P _{11a}	t_3	P _{11b}	-	P _{11a}	t_1	P _{11b}	-
	P _{12a}	t_3	P _{12b}	t_5	P _{12a}	t_1	P _{12b}	-
	P _{13a}	t_2	P _{13b}	t_3	P _{13a}	-	P _{13b}	t_4
	P _{14a}	t_2	P _{14b}	-	P _{14a}	t_5	P _{14b}	-
	P _{15a}	t_1	P _{15b}	t_4	P _{15a}	t_1	P _{15b}	-
	P _{16a}	t_2	P _{16b}	-	P _{16a}	t_4	P _{16b}	-
	P _{17a}	t_1	P _{17b}	t_5	P _{17a}	t_2	P _{17b}	-
	P _{18a}	t_1	P _{18b}	t_5	P _{18a}	t_2	P _{18b}	-
	P _{19a}	t_5	P _{19b}	-	P _{19a}	-	P _{19b}	-
	P _{20a}	-	P _{20b}	-	P _{20a}	-	P _{20b}	-
	P _{21a}	t_5	P _{21b}	-	P _{21a}	-	P _{21b}	-

Table 8.6 shows the quantity of projects and the capital expenditure along the planning horizon. Optimal Plan 1 includes 23 projects and represents the portfolio that maximises the overall infrastructure's IVI during the planning period utilising the available capital of 665,000€. This plan displays an efficient way to apply the capital, aiming to raise the infrastructure's IVI.

A total of 15 projects are included in Optimal Plan 2. According to this plan, 488,519€ is the minimum capital necessary to maintain the IVI of the infrastructure above the recommended limit of 40% and below 60% along all the planning horizon. The outcomes of Optimal Plan 2 show that it is possible to save 26.5% of the available capital and still maintain the overall IVI within the desired range.

Note that the investments for ventilation assets coded as P_{17a} and P_{18a} are both planned for t_1 in Optimal Plan 1 and for t_2 in Optimal Plan 2. The set P_{17b} and P_{18b} was also selected together for t_5 for Optimal Plan 1, but in this case, neither one was selected for Optimal Plan 2. In all the situations that those pairs of projects could be selected, they were selected together, which means that they can be managed as a unique project.

Figure 8.3 presents the blox-plot of assets' IVI values considering a no-investment scenario and both optimal plans. With no investments applied to assets, the average IVI is 37.0%. Optimal

Table 8.6: Number of projects and budget per year of the planning horizon of Optimal Plans 1 and 2

Year	Optimal Plan 1		Optimal Plan 2	
	Projects (No.)	Budget (€)	Projects (No.)	Budget (€)
t_1	7	199,331	6	150,531
t_2	4	198,656	4	72,000
t_3	5	133,062	0	0
t_4	2	67,062	3	158,925
t_5	5	66,531	2	107,063
Total	23	664,643	15	488,519

Plan 1 can increase the average IVI to 44.5%. This is the maximum possible increment with the company's available budget.

In Optimal Plan 2, the average IVI of the individual assets reaches 42.4%, which represents a 5% reduction over the result of Optimal Plan 1, with savings of 26.5% in the capital. The box-plot for Optimal 2 Plan shows that the data's median is below 40.0%, meaning that more than half of the assets present an IVI value lower than 40.0%, even though the infrastructure's IVI is kept within the recommended range.

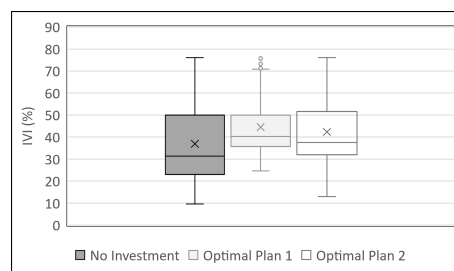


Figure 8.3: Distribution of IVI individual values for each scenario in the planning horizon (t_1 to t_5).

Suppose the company sets a more challenging objective to raise the IVI of individual assets above 40% for the planning period. This scenario was analysed using the alternative constraints (8.22) detailed in subsection 8.3.2.2. The capital required is 78.6% higher than planned, totalling 1,187,838€. Besides the more significant amount of necessary investments, the companies often prefer to keep the IVI of the complete infrastructure within the control bounds, instead of targeting IVI ranges for individual assets. Low-IVI assets can be tolerated, since the companies usually monitor closely the assets' performance employing reliable estimates of risk.

The resulting IVI values for the overall infrastructure and equipment groups are presented in Figure 8.4. The graphs in Figure 8.4 compare the overall IVI and asset group's IVI in Optimal Plans 1 and 2, generated from both optimisation models. The comparison is also performed with a no-investment condition. If the optimal plans and the no-investment scenario are compared, the graphs show that investments are crucial to maintain the IVI at acceptable levels. If no investments are performed, the assets' deterioration will decline the IVI. It can also be noticed that most of the

time, Optimal Plan 1, with a higher amount of capital invested in asset projects, can keep the IVI at higher levels than Optimal Plan 2.

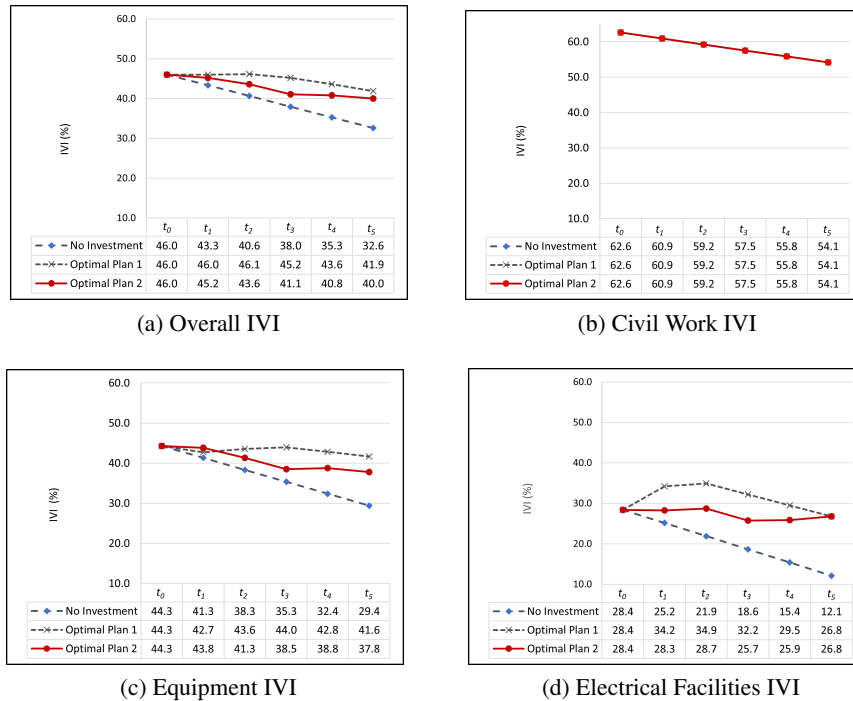


Figure 8.4: Overall and group IVI in different scenarios: zero investment and Optimal Plans 1 and 2.

The overall infrastructure's IVI is presented in Figure 8.4a. This graph shows that both Optimal Plans can keep the overall IVI over time at an acceptable level (between 40.0% and 60.0%).

Examining the IVI in the different component groups, no investments were proposed for civil work assets during the considered time frame, so the IVI for the civil work group decreases and is identical in all the cases, as shown in Figure 8.4b. Moreover, at the end of t_6 , it is still at an adequate level (54.1%).

Figure 8.4c displays the equipment group. As it represents 15 out of 21 assets, the trends observed for this group are similar to the overall trends observed in Figure 8.4a. The majority of projects for both optimal plans involve assets from this group. In Optimal Plan 1, this group presents an acceptable IVI for all years. However, this group presents values of IVI under the lower bound of 40.0% for t_3 , t_4 and t_5 in Optimal Plan 2.

Finally, Figure 8.4d shows that the electrical facilities group's IVI drops from 28.4% to 12.1% with no investment in five years, and the available capital in both plans is insufficient to keep the IVI at an acceptable level. The observed low-IVI levels indicate the necessity to monitor the risks more closely in electrical facilities.

The considerations about results of IVI for groups of similar components and overall infrastructures are frequent in the literature (Alegre et al., 2014; Vieira et al., 2020a,b; Cabrera Rochera

et al., 2019). Those approaches help to focus managers' attention on problematic areas and compare different infrastructures. However, a closer assessment of individual assets' IVI may be useful to accurately identify areas of significant risks. If a group of assets or infrastructure presents an acceptable IVI, it does not necessarily mean that there are no potential problems among their components.

8.5.3 Results of multi-objective optimisation

The genetic algorithm was implemented using Python Programming Language. The average computational time was approximately one hour. It is important to note that the computational times of the genetic algorithm cannot be directly compared with CPLEX. The genetic algorithm was designed to address a multi-objective optimisation problem, whereas the MILP models solving using CPLEX address a single objective optimisation problem. As discussed in subsection 8.3.3, besides generating Optimal Plans 1 and 2, additional project plans were identified using a multi-objective technique based on NSGA-II. The trade-off between the objectives of Optimisation Models 1 and 2 is presented in Figure 8.5, where Plans A, B, C and D represent the alternate project plans. Those alternative asset investment plans are made available to decision-makers so that they may find new possibilities that are more suited to their strategic goals. As seen in Figure 8.5, the alternate plans represent intermediate solutions between the objectives of Optimal Plans 1 and 2.

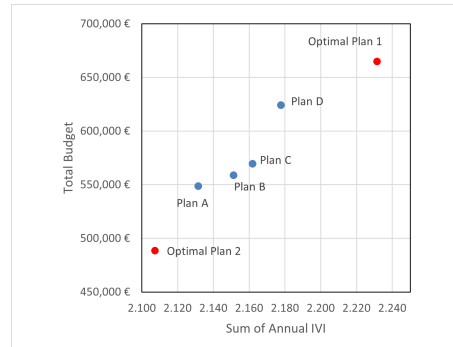


Figure 8.5: Objective function values from Optimal Plans 1 and 2 and alternate project plans from multi-objective optimisation.

The number of projects and capital necessary to implement them in each year are displayed in Table 8.7. The list of selected projects in Plans A, B, C and D is presented in Table E.2 in Appendix E.3.

The trade-offs between the optimal solutions for each of the alternative plans, can be obtained by solving equation (8.30) to determine the weights γ_1 and γ_2 for the linear combination of optimal values in Optimisation Models 1 and 2, where j represents each of the alternate plans A, B, C and D. Table 8.8 displays the trade-off values.

$$\begin{pmatrix} IVI_{Planj}^{sum} \\ C_{Planj}^{total} \end{pmatrix} = \gamma_1 \times \begin{pmatrix} IVI_{opt1}^{sum} \\ C_{opt1}^{total} \end{pmatrix} + \gamma_2 \times \begin{pmatrix} IVI_{opt2}^{sum} \\ C_{opt2}^{total} \end{pmatrix}, \quad j = A, B, C, D. \quad (8.30)$$

Table 8.7: Alternate project plans from multi-objective optimisation

Year	Plan A		Plan B		Plan C		Plan D	
	Projects (No.)	Budget (€)	Projects (No.)	Budget (€)	Projects (No.)	Budget (€)	Projects (No.)	Budget (€)
t_1	5	127,233	3	149,063	5	196,656	4	186,125
t_2	4	190,125	4	182,223	7	161,423	4	183,023
t_3	3	73,423	5	83,278	2	75,062	4	75,809
t_4	2	68,000	2	68,000	2	68,000	4	108,000
t_5	3	90,000	3	76,340	2	68,340	3	71,278
Total	17	548,781	17	558,903	18	569,482	19	624,235

Table 8.8: Trade-off in Alternate Solutions compared to Optimal Solutions

Optimal Plans				
Plan j	IVI_{opt}^{sum}	C_{opt}^{total}		
Optimal Plan 1	2.232	664,643		
Optimal Plan 2	2.107	488,519		
Alternate Plans			Trade-offs	
Plan j	IVI_{Planj}^{sum}	C_{Planj}^{total}	γ_1	γ_2
Plan A	2.132	548,781	62.5%	37.5%
Plan B	2.151	558,903	59.0%	41.0%
Plan C	2.162	569,482	53.6%	46.4%
Plan D	2.178	624,235	17.7%	82.3%

The results show that the influence of Optimisation Model 1 is higher in the alternate plans A, B and C and the influence of Optimisation Model 2 is higher in Plan D. The choice of the solution to be implemented will depend on the strategic plan defined by the company, based on the priority assigned to each of the objectives.

8.6 Conclusion

This work provided a novel approach to select capital investment initiatives for asset management in multi-asset systems, using the Infrastructure Value Index. Developing new formulations that reflect the impact of investment projects on assets' conditions made it possible to establish procedures based on mixed-integer linear programming and evolutionary models and test them using real-world data from a Portuguese water supply company.

Previous studies have evaluated the effect of investment projects on the Infrastructure Value Index but have not considered the possibility of improving it by optimal capital allocation. This work fills this gap in the literature by introducing MILP optimisation models to determine optimal investment project plans using two distinct objectives: IVI maximisation and capital expenses minimisation. Furthermore, the trade-offs between the models are discussed and alternate project plans are generated using a multi-objective approach based on genetic algorithms. The proposed models can be tailored to each situation by incorporating specific constraints according to the company's goals.

The optimisation models were applied to a real-world case study and the outcomes were discussed. The results showed that the proposed approach could effectively prioritise investment projects in assets. The information required to develop the models includes estimating some parameters for all the project candidates, and the proper characterisation of the assets to define residual lives, useful lives and replacement costs. This methodology can be generalised to other sectors where decision-making tools are important to support asset management.

The project parameters, e.g. residual life increment coefficients, decommissioning coefficients, and project capital expenses can be reasonably determined by the company's technical staff. This evaluation is facilitated by their specific knowledge about the assets and can lead to precise capital allocation forecasts when running the optimisation models. The models' feasibility depends on the input project data. For example, in Optimisation Model 2, where a minimum level of IVI is demanded, the model may be infeasible if the project investments and decommissioning coefficients are too low. On the other hand, if the parameters are estimated at a too high level, the resultant investment will not reflect the minimum capital necessary to maintain the IVI at a certain level. This work considers that a portfolio of potential project candidates is given by the company, so the determination of optimum levels for project parameters is out of our scope and can be addressed in future developments.

The proposed optimisation models reinforce the role of the IVI as the leading driver for selecting asset projects. However, some limitations may be present in that approach. One of them is related to the estimation of risks. A primary objective of any investment plan is to decrease the risk of asset failures. This assumption is implicitly present in the developed models under the estimation of service lives since the models assume that lower values of the IVI imply higher risks, mainly due to the asset's ageing. However, risks can appear from different sources, under several circumstances other than ageing affecting assets' operational conditions. Another limitation concerns the value that potential assets' renewal or replacement initiatives can add to the business. Those actions can bring new functionalities, technological advances, or other efficiency gains that the presented models do not consider.

The IVI is a simple and easily communicable metric, but it does not take into account other useful aspects in project selection, such as the functional condition of the asset, its structural state, hydraulic, environmental or customer satisfaction performance. However, despite these limitations, the IVI has the potential to guide investments aimed to enhance infrastructures' sustainability and reliability in a global and generalised manner, providing support for managers that can be complemented by more detailed analysis.

Future developments may consider new optimisation drivers complementary to those reflected in the current models. Further research is also needed to address the uncertainties in the IVI calculation related to key concepts such as replacement costs, depreciation rates, and service life.

CHAPTER 9

Conclusions

This chapter provides the main conclusions drawn from this thesis. Section 9.1 discusses the extent to which the research objectives were achieved and the primary contributions of this doctoral research. In Section 9.2, the limitations of this research are acknowledged. Section 9.3 highlights the key insights that emerged from the studies undertaken. Finally, Section 9.4 suggests potential areas for future research.

9.1 Fulfilment of the research objectives

The primary objective of this thesis was to develop innovative models using mathematical programming techniques, specifically optimisation and frontier methods, to address management challenges faced by water utilities. This objective was successfully achieved by developing tools that tackle cost-efficiency, service quality, and asset management challenges and by applying these tools in practical cases using real-world data from the water sector.

The thesis consists of five studies, organised into chapters, which involve methodological developments and practical demonstrations using real data. These studies align with the defined objective of the thesis, and the accomplishment of the objective through these studies is presented in chapters 4, 5, 6, 7, and 8. The subsequent paragraphs detail the achievements of each study in addressing the management challenges faced by water utilities.

Chapter 4 explored the assessment of cost-efficiency of water supply and wastewater utilities over a five-year period. A method was proposed to guide improvements in cost-efficiency within the water sector, using DEA models that were applied to a sample of utilities.

Chapter 5 aimed to address the service quality challenge by offering a decision support tool, based on a BoD model, to evaluate the quality of services provided by the utilities from the perspective of customers. The performance trends over a span of six years are analysed.

Chapter 6 provided a method to assess water utilities' asset management by integrating two different perspectives that focus on managerial practices and operational results. The proposed method employs BoD composite indicators in a benchmarking analysis conducted over a five-year period. This enables utilities to compare their performance over time and against other utilities.

In Chapter 7, the asset management challenge is also addressed, and the main innovative contribution of this chapter is a tool to identify suitable peers and individual targets for benchmarking asset management performance, using BoD composite indicators.

Chapter 8 developed a method to select infrastructure capital projects of water utilities, focusing on the asset management challenge as well. This method employs optimisation techniques, namely mixed integer linear programming (MILP) and evolutionary algorithms.

The contributions detailed in each chapter validate the achievement of the thesis's main objective by providing decision support tools to address the proposed management challenges of the utilities.

9.2 Limitations of the research

The research presented in this thesis has successfully achieved all the proposed objectives. However, it is important to acknowledge that there are limitations to the studies conducted. The specific limitations in each study are discussed in their respective chapters, but some general limitations are highlighted here.

An important limitation to note in this thesis is the availability and quality of data. The decision models developed require accurate and comprehensive data for analysis. However, in the water sector, data collection and recording can often be incomplete or inconsistent, posing challenges to the application of the models.

In the empirical cases of the studies, the data was obtained from reliable sources such as regulators or utilities, but it did not always meet the exact requirements for building decision support tools. For example, in Chapter 4, the metric *raw water quality* used in the decision model had to be developed by the regulator as it was not available initially. Additionally, Chapter 6 faced difficulties due to the limited sample size, and Chapter 5 lacked a transparency metric, highlighting the limitations posed by the data available.

The stakeholder collaboration varied across the different chapters of the study. The most extensive collaboration occurred in Chapter 4, where close collaboration was established with a water sector regulatory authority. Additionally, Chapter 8 received validation from the participating utility, AdDP. However, in Chapter 5, the collaboration was limited to consulting water sector experts during specific stages of the research. In the remaining studies, collaboration with regulators and utilities was not possible. Incorporating preferences and insights from regulators and utilities in these studies could have significantly enhanced the accuracy and practicality of the results. By involving stakeholders closely, a more comprehensive understanding of the industry's needs and requirements could have been obtained, leading to more meaningful outcomes.

Overall, while the limitations mentioned above did not significantly impact the achievement of the proposed objectives, they do provide opportunities for future research and improvements in the application of decision support tools in the water sector.

9.3 Insights from the illustrative applications

The improvements in methodology demonstrated in this thesis enabled the acquisition of valuable insights regarding the management of water utilities. Those main insights collected from the

illustrative applications are presented in the following paragraphs.

Insight 1: Prioritising the collection of comprehensive and reliable data from utilities can facilitate informed decision-making and yield numerous benefits.

All the studies presented in this thesis highlight the importance of robust data collection and analysis. Investing in a comprehensive data collection and recording process can provide significant benefits by allowing the data to be utilised in decision support tools to generate insights for both the organisation and the broader sector. However, it is important to note that simply collecting more data does not always lead to better decision-making outcomes. It is critical to identify the most important data and focus on collecting and analysing those in a structured and efficient manner. Furthermore, the utilisation of decision support tools can help to streamline data analysis and identify patterns and trends that may not be immediately apparent through manual analysis.

Insight 2: By combining internal and external benchmarking, organisations can identify significant opportunities for improvement.

Chapters 4, 5, and 6 demonstrate the effectiveness of combining internal and external benchmarking to identify improvement opportunities. By using a combination of the utility and year to form DMUs, these studies allow for comparisons between different utilities as well as the utility's performance in different years. This approach enables a utility to not only compare itself with peers but also to evaluate its own performance over time, leading to a more comprehensive analysis of improvement opportunities. Chapter 4 highlights the effectiveness of this approach, as cost-efficiency benchmarking using a conditional approach identified improvement opportunities only within utilities and their own performances in different years, which can be considered a form of internal benchmarking.

Insight 3: Customer-oriented performance assessments can pinpoint precise opportunities to enhance quality and improve overall performance.

Chapter 5 highlights the importance of adopting a customer-centric approach to service quality measurement, which can provide more specific and detailed guidance on where improvements can be made. By focusing on the customer's perspective, utilities can pinpoint precise opportunities to enhance quality and improve overall performance. This approach encourages utilities to continuously improve their services, foster trust and satisfaction among customers.

Insight 4: Implementing a structured asset management system may not yield immediate improvements in operational performance.

The evaluation of asset management performance was conducted through two different perspectives in Chapters 6 and 7: management practices and operational results. This approach proved to be effective in providing insights into the benefits of investment in infrastructure management practices over the long term. As highlighted in the literature, investment in infrastructure management practices takes time to yield tangible outcomes. This finding is further supported by the empirical studies conducted in these chapters. The results reveal that favourable outcomes in management practices do not always translate immediately into positive operational results. Thus, a long-term approach to implementing asset management systems, with continuous monitoring and evaluation of their effectiveness, is crucial for achieving positive operational results.

Insight 5: Management systems and different areas of intervention present significant impact to utilities' performance.

In Chapters 4, 6, and 7, management models (concession, delegation, or direct management) and the typology of intervention areas (rural, urban, semi-urban) were considered as contextual variables to improve the fairness of comparisons between utilities. The results indicate that these factors significantly impact utilities' performance in terms of cost efficiency and asset management. Specifically in the case of asset management, both retail (Chapter 7) and wholesale operations (Chapter 6) were significantly impacted by these contextual variables. Therefore, to gain a comprehensive understanding of utility performance in these areas, it is important to consider these factors.

Insight 6: Customised performance targets based on benchmarking exercises using actual performance data may be more effective in guiding improvements than generic goals.

In Chapter 7, the BoD technique was used to establish performance targets for utilities in terms of asset management. By comparing the specific targets derived from the analysis with the general goals suggested by regulatory authorities, we observe that the latter are often overly ambitious in comparison to the typical performance of the sector. This implies that attaining these generic goals may not be a practical approach for utilities. The tailored target-setting approach provided by the BoD tool offers a more effective way for utilities to enhance their performance. By tailoring targets to each utility's current level of performance, the tool provides a realistic and achievable framework for improvement.

Insight 7: Identifying a peer group for benchmarking asset management practices can provide valuable guidance and recommendations, particularly in a highly fragmented business sector.

In Chapter 7, we explore the use of benchmarking to assess asset management performance in a diverse and fragmented retail water market. To identify suitable peers for comparison and improvement, we developed a method that provides specific efficient peers for each utility. This is particularly relevant in a highly fragmented business sector, where identifying a suitable peer group can be challenging. This approach proves to be valuable in guiding utilities and helping them identify their most appropriate peers for benchmarking purposes, and gain awareness into best practices and recommendations for improvement.

Insight 8: Optimisation techniques can be an effective tool to guide investment decisions.

In Chapter 8, we present optimisation tools that were developed to assist with the decision-making process for defining an investment project portfolio for water systems' infrastructure. This model can be a valuable resource in guiding investment decisions, especially when combined with other methods that can provide additional drivers for selecting the most appropriate project plan.

9.4 Directions to further research

In previous chapters, several directions for future research have been identified. In this section, we highlight some key features that can guide further investigation in this field. The use of decision

support tools in water utility management presents a broad range of research possibilities that can be explored in numerous ways.

One promising avenue for research is to further investigate the impact of contextual variables, such as management systems and intervention areas, on the performance of utilities. A more comprehensive understanding of how these factors influence performance can provide valuable insights for the sector's management. Additionally, by collecting and analysing necessary information to characterise the environment in which utilities operate, other contextual variables could be evaluated, leading to more effective management of the sector.

Another area for further research is gaining a deeper understanding of the structure of the water sector. This involves comparing public and private operations, determining optimal operational size, and deciding on the scope of operations and vertical integration. For example, it remains unclear whether it is advantageous for a utility to operate in both water supply and sanitation or provide services to both wholesale and retail markets.

Decision support tools can be more effective when incorporating stakeholder preferences. Stakeholder feedback can be used to develop more tailored decision support tools that address the needs of a wide range of stakeholders, including utility management, customers, and regulators.

Additionally, the inclusion of more drivers for investment decisions in infrastructure can complement and expand the model developed using the Infrastructure Value Index, leading to more precise project portfolios.

Another important area to be incorporated into decision support tools is risk management. Risk management can help utilities identify and manage potential risks associated with their operations, such as financial, operational, or environmental risks. This can lead to better decision-making, improved performance, and increased resiliency.

Decision support tools can also address emerging challenges in the water sector, such as the increasing need for digitalisation and integration with new connectivity technologies, as well as integration with environmental issues and the circular economy. By incorporating these challenges into decision support tools, utilities can ensure they are prepared to tackle the challenges of the future.

Finally, comparing utility performance in different countries is another promising area for research. This can help utilities identify best practices in other countries and adapt them to their own operations, leading to improved performance and efficiency.

Appendix to Chapter 4

A.1 Descriptive statistics

A.1.1 Variables

Table A.1: Descriptive statistics of the variables used in WS MODELS.

Year	Variable	Mean	Standard deviation	Minimum	Maximum
2017	x_1^{WS}	12,395,102.16	10,033,834.25	395,495.00	26,460,650.66
	y_1^{WS}	63,980,827.14	68,994,925.54	2,151,337.00	229,002,657.80
	y_2^{WS}	95,400,689.13	124,276,267.73	133,220.00	411,152,726.57
	y_3^{WS}	363,978.80	315,610.54	13,100.00	831,458.00
	y_4^{WS}	1,038.84	1,196.51	26.80	3,592.50
	z_1^{WS}	2.58	1.04	1.01	4.00
2018	x_1^{WS}	12,279,225.73	9,902,925.74	452,405.58	27,994,392.92
	y_1^{WS}	61,546,785.64	65,922,840.17	1,671,349.70	218,116,734.10
	y_2^{WS}	75,926,301.82	74,837,040.63	97,320.00	216,991,501.40
	y_3^{WS}	363,978.80	315,610.54	13,100.00	831,458.00
	y_4^{WS}	1,038.84	1,196.51	26.80	3,592.50
	z_1^{WS}	2.62	1.09	1.01	4.00
2019	x_1^{WS}	12,534,473.63	10,031,587.68	434,584.29	28,867,824.39
	y_1^{WS}	63,238,860.53	66,926,146.21	2,295,527.00	221,836,249.50
	y_2^{WS}	79,291,274.48	78,851,433.83	92,899.28	227,531,526.53
	y_3^{WS}	363,978.80	315,610.54	13,100.00	831,458.00
	y_4^{WS}	1,038.84	1,196.51	26.80	3,592.50
	z_1^{WS}	2.38	1.16	1.00	4.00
2020	x_1^{WS}	12,885,563.17	10,454,720.57	493,640.65	30,304,818.28
	y_1^{WS}	63,486,330.01	66,564,159.78	1,853,111.00	221,124,927.50
	y_2^{WS}	87,498,453.77	91,680,391.39	90,282.00	291,069,399.21
	y_3^{WS}	363,978.80	315,610.54	13,100.00	831,458.00
	y_4^{WS}	1,038.84	1,196.51	26.80	3,592.50
	z_1^{WS}	2.35	1.16	1.00	4.00
2021	x_1^{WS}	12,220,446.01	9,690,404.96	462,896.00	26,894,013.72
	y_1^{WS}	63,376,911.69	66,530,277.81	1,974,214.00	221,716,594.60
	y_2^{WS}	82,765,968.47	79,201,694.49	80,448.00	238,510,635.86
	y_3^{WS}	363,978.80	315,610.54	13,100.00	831,458.00
	y_4^{WS}	1,038.84	1,196.51	26.80	3,592.50
	z_1^{WS}	2.38	1.17	1.00	4.00

Table A.2: Descriptive statistics of the variables used in WT MODELS.

Year	Variable	Mean	Standard deviation	Minimum	Maximum
2017	x_1^{WT}	13,436,619.49	13,472,594.14	412,369.17	40,721,908.47
	y_1^{WT}	42,102,229.49	52,517,519.75	4,271,902.30	183,032,070.20
	y_2^{WT}	39,564,638.97	49,220,985.12	198,887.00	149,159,693.48
	y_3^{WT}	321,232.10	332,894.80	17,489.00	1,127,557.00
	y_4^{WT}	523.84	530.60	31.20	1,645.00
	z_1^{WT}	3.59	1.51	1.00	5.00
2018	x_1^{WT}	13,965,105.88	13,493,353.61	381,752.16	40,073,630.51
	y_1^{WT}	47,561,707.67	55,896,640.65	4,542,814.00	194,233,441.50
	y_2^{WT}	29,316,932.93	48,280,960.23	278,201.00	152,651,482.29
	y_3^{WT}	321,232.10	332,894.80	17,489.00	1,127,557.00
	y_4^{WT}	523.84	530.60	31.20	1,645.00
	z_1^{WT}	3.59	1.51	1.00	5.00
2019	x_1^{WT}	14,622,204.20	14,300,805.38	1,235,023.21	43,327,904.80
	y_1^{WT}	46,021,939.12	53,178,253.80	4,241,844.20	185,062,474.90
	y_2^{WT}	46,484,766.47	65,437,777.76	286,984.00	184,199,337.79
	y_3^{WT}	321,903.70	332,220.02	24,205.00	1,127,557.00
	y_4^{WT}	520.90	533.55	28.00	1,645.00
	z_1^{WT}	3.99	1.26	1.00	5.00
2020	x_1^{WT}	14,013,753.63	13,757,954.24	472,208.75	45,183,937.02
	y_1^{WT}	44,040,373.08	51,521,976.35	4,908,142.00	193,585,060.80
	y_2^{WT}	52,290,736.79	80,634,323.06	311,960.00	275,252,931.11
	y_3^{WT}	296,744.08	313,109.01	17,489.00	1,127,557.00
	y_4^{WT}	479.03	500.67	28.00	1,645.00
	z_1^{WT}	3.65	1.44	1.00	5.00
2021	x_1^{WT}	14,787,598.11	14,392,195.05	507,821.70	47,817,730.33
	y_1^{WT}	46,818,113.98	51,478,321.80	4,843,681.00	184,164,595.40
	y_2^{WT}	45,322,787.43	59,286,303.73	327,424.00	185,498,401.74
	y_3^{WT}	296,744.08	313,109.01	174,89.00	1,127,557.00
	y_4^{WT}	479.03	500.67	28.00	1,645.00
	z_1^{WT}	3.65	1.44	1.00	5.00

Table A.3: Management model and typology of intervention area per model.

Descriptive contextual variable	Description	Relative frequency
z_2^{WS}	Concession	70%
	Delegation	30%
z_3^{WS}	Predominantly rural area	30%
	Moderately urban area	50%
	Predominantly urban area	20%
z_2^{WT}	Concession	83%
	Delegation	8%
	Direct management	8%
z_3^{WT}	Predominantly rural area	25%
	Moderately urban area	50%
	Predominantly urban area	25%

A.1.2 Efficiency scores

Table A.4: Descriptive statistics of the efficiency scores generated by WS MODELS.

Model	Sample perspective	Type	Mean	Standard deviation	Minimum	Maximum
WS-RU	Full	-	1.0660	0.2650	0.8731	2.5116
	MANAGEMENT MODEL	Concession	1.0457	0.1826	0.8901	1.9882
		Delegation	1.1132	0.4017	0.8731	2.5116
	TYPOLOGY OF THE INTERVENTION AREA	Direct management	-	-	-	-
		Predominantly rural area	1.2379	0.4383	0.9056	2.5116
		Moderately urban area	1.0012	0.0620	0.8901	1.2176
		Predominantly urban area	0.9702	0.0444	0.8731	1.0002
WS-RC	Full	-	0.9835	0.0299	0.8731	1.0000
	MANAGEMENT MODEL	Concession	0.9868	0.0247	0.9043	1.0000
		Delegation	0.9757	0.0394	0.8731	1.0000
	TYPOLOGY OF THE INTERVENTION AREA	Direct management	-	-	-	-
		Predominantly rural area	0.9916	0.0188	0.9388	1.0000
		Moderately urban area	0.9832	0.0274	0.9043	1.0000
		Predominantly urban area	0.9719	0.0452	0.8731	1.0000

Table A.5: Descriptive statistics of the efficiency scores generated by WT MODELS.

Model	Sample perspective	Type	Mean	Standard deviation	Minimum	Maximum
WT-RU	Full	-	1.0837	0.3332	0.8266	3.0230
	MANAGEMENT MODEL	Concession	1.0509	0.3146	0.8266	3.0230
		Delegation	1.0520	0.0327	1.0285	1.1084
	TYPOLOGY OF THE INTERVENTION AREA	Direct management	1.6406	0.4701	1.1009	1.9607
		Predominantly rural area	1.2464	0.5277	0.9787	3.0230
		Moderately urban area	1.0576	0.2627	0.8266	1.9607
		Predominantly urban area	0.9755	0.0578	0.8380	1.0474
WT-RC	Full	-	0.9881	0.0321	0.8380	1.0000
	MANAGEMENT MODEL	Concession	0.9861	0.0344	0.8380	1.0000
		Delegation	1.0000	0.0000	1.0000	1.0000
	TYPOLOGY OF THE INTERVENTION AREA	Direct management	1.0000	0.0000	1.0000	1.0000
		Predominantly rural area	0.9930	0.0204	0.9258	1.0000
		Moderately urban area	0.9984	0.0061	0.9703	1.0000
		Predominantly urban area	0.9664	0.0523	0.8380	1.0000

Appendix to Chapter 5

B.1 Results for water supply utilities - WUSQI and contributions of each dimension

Table B.1: Water supply utilities - WUSQI and contributions of each dimension.

Company	Year	Relative importance of WUSQI dimensions					
		CI	Inclusiveness	Reliability	Safety	Responsiveness	Transparency
AdSA	2016	0.952	80.0%	5.0%	5.0%	5.0%	5.0%
	2017	0.958	80.0%	5.0%	5.0%	5.0%	5.0%
	2018	0.957	80.0%	5.0%	5.0%	5.0%	5.0%
	2019	0.958	80.0%	5.0%	5.0%	5.0%	5.0%
	2020	0.959	80.0%	5.0%	5.0%	5.0%	5.0%
	2021	0.955	80.0%	5.0%	5.0%	5.0%	5.0%
AdA	2016	0.972	10.0%	5.0%	75.0%	5.0%	5.0%
	2017	0.970	10.0%	5.0%	75.0%	5.0%	5.0%
	2018	0.846	80.0%	5.0%	5.0%	5.0%	5.0%
	2019	0.984	10.0%	5.0%	65.0%	15.0%	5.0%
	2020	0.977	10.0%	5.0%	75.0%	5.0%	5.0%
	2021	0.986	10.0%	5.0%	65.0%	15.0%	5.0%
AdCL	2016	0.965	10.0%	5.0%	75.0%	5.0%	5.0%
	2017	0.978	10.0%	5.0%	65.0%	15.0%	5.0%
	2018	0.982	70.0%	5.0%	5.0%	15.0%	5.0%
	2019	0.856	80.0%	5.0%	5.0%	5.0%	5.0%
	2020	0.875	70.0%	5.0%	5.0%	15.0%	5.0%
	2021	0.875	70.0%	5.0%	5.0%	15.0%	5.0%
AdDP	2017	0.993	70.0%	5.0%	5.0%	15.0%	5.0%
	2018	0.998	70.0%	5.0%	5.0%	15.0%	5.0%
	2019	0.995	70.0%	5.0%	5.0%	15.0%	5.0%
	2020	0.996	70.0%	5.0%	5.0%	15.0%	5.0%
	2021	1.000	70.0%	5.0%	5.0%	15.0%	5.0%
AdN	2016	0.884	10.0%	5.0%	75.0%	5.0%	5.0%
	2017	0.942	10.0%	5.0%	75.0%	5.0%	5.0%
	2018	0.840	10.0%	5.0%	65.0%	15.0%	5.0%
	2019	0.961	10.0%	5.0%	65.0%	15.0%	5.0%
	2020	0.961	10.0%	5.0%	65.0%	15.0%	5.0%
	2021	0.966	10.0%	5.0%	65.0%	15.0%	5.0%
AdVT	2016	0.901	10.0%	5.0%	65.0%	15.0%	5.0%
	2017	0.840	10.0%	5.0%	65.0%	15.0%	5.0%
	2018	0.841	10.0%	5.0%	65.0%	15.0%	5.0%
	2019	0.900	10.0%	5.0%	65.0%	15.0%	5.0%
	2020	0.902	10.0%	5.0%	65.0%	15.0%	5.0%
	2021	0.842	10.0%	5.0%	65.0%	15.0%	5.0%
AdVouga	2016	0.938	10.0%	5.0%	75.0%	5.0%	5.0%
	2017	0.935	10.0%	5.0%	75.0%	5.0%	5.0%
	2018	0.945	10.0%	5.0%	5.0%	5.0%	75.0%
	2019	0.945	10.0%	5.0%	5.0%	5.0%	75.0%
	2020	0.943	10.0%	5.0%	5.0%	5.0%	75.0%
	2021	0.941	10.0%	5.0%	5.0%	5.0%	75.0%
AgDA	2016	0.856	70.0%	5.0%	5.0%	15.0%	5.0%
	2017	0.843	70.0%	5.0%	5.0%	15.0%	5.0%
	2018	0.841	70.0%	5.0%	5.0%	15.0%	5.0%
	2019	0.886	80.0%	5.0%	5.0%	5.0%	5.0%
	2020	0.896	70.0%	5.0%	5.0%	15.0%	5.0%
	2021	0.917	80.0%	5.0%	5.0%	5.0%	5.0%
EPAL	2016	0.851	10.0%	5.0%	65.0%	15.0%	5.0%
	2017	0.850	10.0%	5.0%	65.0%	15.0%	5.0%
	2018	0.976	10.0%	5.0%	65.0%	15.0%	5.0%
	2019	0.975	10.0%	5.0%	65.0%	15.0%	5.0%
	2020	0.972	10.0%	5.0%	65.0%	15.0%	5.0%
	2021	0.974	10.0%	5.0%	65.0%	15.0%	5.0%
ICOVI	2016	0.939	80.0%	5.0%	5.0%	5.0%	5.0%
	2017	0.944	80.0%	5.0%	5.0%	5.0%	5.0%
	2018	0.944	80.0%	5.0%	5.0%	5.0%	5.0%
	2019	0.945	80.0%	5.0%	5.0%	5.0%	5.0%
	2020	0.946	80.0%	5.0%	5.0%	5.0%	5.0%
	2021	0.830	80.0%	5.0%	5.0%	5.0%	5.0%

B.2 Results for wastewater utilities - WUSQI and contributions of each dimension.

Table B.2: Wastewater utilities - WUSQI and contributions of each dimension.

Company	Year	CI	Relative importance of WUSQI dimensions				
			Inclusiveness	Reliability	Safety	Responsiveness	Transparency
AdSerra	2016	0.992	35.10%	38.97%	5.00%	5.09%	15.83%
	2017	0.997	34.08%	39.03%	5.65%	5.10%	16.14%
	2018	1.000	34.08%	39.03%	5.65%	5.10%	16.14%
	2019	0.999	34.08%	39.03%	5.65%	5.10%	16.14%
	2020	1.000	10.00%	38.30%	5.00%	5.50%	41.20%
AdSA	2021	1.000	35.10%	38.97%	5.00%	5.09%	15.83%
	2016	1.000	37.12%	38.57%	5.00%	5.00%	14.31%
	2017	1.000	32.57%	46.37%	5.00%	5.00%	11.06%
	2018	0.932	10.00%	5.00%	5.00%	5.00%	75.00%
	2019	1.000	40.83%	44.17%	5.00%	5.00%	5.00%
AdA	2020	0.996	40.83%	44.17%	5.00%	5.00%	5.00%
	2021	0.922	80.00%	5.00%	5.00%	5.00%	5.00%
	2016	0.906	80.00%	5.00%	5.00%	5.00%	5.00%
	2017	0.894	70.00%	5.00%	5.00%	15.00%	5.00%
	2018	0.908	80.00%	5.00%	5.00%	5.00%	5.00%
AdCL	2019	0.872	10.00%	5.00%	75.00%	5.00%	5.00%
	2020	0.888	10.00%	5.00%	65.00%	15.00%	5.00%
	2021	0.881	10.00%	5.00%	75.00%	5.00%	5.00%
	2016	0.950	80.00%	5.00%	5.00%	5.00%	5.00%
	2017	0.941	10.00%	5.00%	75.00%	5.00%	5.00%
AdN	2018	0.917	10.00%	5.00%	75.00%	5.00%	5.00%
	2019	0.928	10.00%	5.00%	75.00%	5.00%	5.00%
	2020	0.929	10.00%	5.00%	65.00%	15.00%	5.00%
	2021	0.886	70.00%	5.00%	5.00%	15.00%	5.00%
	2016	0.902	10.00%	5.00%	75.00%	5.00%	5.00%
AdTA	2017	0.890	10.00%	5.00%	75.00%	5.00%	5.00%
	2018	0.919	10.00%	5.00%	65.00%	15.00%	5.00%
	2019	0.915	10.00%	5.00%	65.00%	15.00%	5.00%
	2020	0.911	10.00%	5.00%	65.00%	15.00%	5.00%
	2021	0.904	10.00%	5.00%	65.00%	15.00%	5.00%
AdVT	2016	0.929	80.00%	5.00%	5.00%	5.00%	5.00%
	2017	0.949	10.00%	5.00%	65.00%	15.00%	5.00%
	2018	0.935	70.00%	5.00%	5.00%	15.00%	5.00%
	2019	0.929	10.00%	5.00%	65.00%	15.00%	5.00%
	2020	0.925	70.00%	5.00%	5.00%	15.00%	5.00%
AgDA	2021	0.951	70.00%	5.00%	5.00%	15.00%	5.00%
	2017	0.959	10.00%	31.46%	38.54%	15.00%	5.00%
	2018	0.939	10.00%	5.00%	65.00%	15.00%	5.00%
	2019	0.993	11.68%	32.12%	36.20%	15.00%	5.00%
	2020	1.000	11.68%	32.12%	36.20%	15.00%	5.00%
AMTSM	2021	0.986	10.25%	40.55%	5.00%	15.00%	29.21%
	2016	0.891	70.00%	5.00%	5.00%	15.00%	5.00%
	2017	0.874	70.00%	5.00%	5.00%	15.00%	5.00%
	2018	0.846	70.00%	5.00%	5.00%	15.00%	5.00%
	2019	0.849	70.00%	5.00%	5.00%	15.00%	5.00%
SIMARSUL	2020	0.800	80.00%	5.00%	5.00%	5.00%	5.00%
	2021	0.878	70.00%	5.00%	5.00%	15.00%	5.00%
	2017	1.000	77.87%	5.00%	5.00%	5.00%	7.13%
	2018	0.845	74.76%	5.00%	6.28%	5.00%	8.96%
	2019	0.836	74.30%	5.00%	5.00%	5.00%	10.70%
SIMDOURO	2020	0.828	80.00%	5.00%	5.00%	5.00%	5.00%
	2021	0.927	80.00%	5.00%	5.00%	5.00%	5.00%
	2017	0.917	70.00%	5.00%	5.00%	15.00%	5.00%
	2018	0.923	70.00%	5.00%	5.00%	15.00%	5.00%
	2019	0.892	70.00%	5.00%	5.00%	15.00%	5.00%
TRATAVE	2020	0.878	70.00%	5.00%	5.00%	15.00%	5.00%
	2021	0.912	70.00%	5.00%	5.00%	15.00%	5.00%
	2017	0.939	10.00%	5.00%	75.00%	5.00%	5.00%
	2018	0.954	10.00%	29.51%	50.49%	5.00%	5.00%
	2019	0.939	10.00%	5.00%	75.00%	5.00%	5.00%
TRATAVE	2020	1.000	10.00%	29.51%	50.49%	5.00%	5.00%
	2021	0.958	10.00%	5.00%	65.00%	15.00%	5.00%
	2016	0.970	80.00%	5.00%	5.00%	5.00%	5.00%
	2017	0.988	70.00%	5.00%	5.00%	15.00%	5.00%
	2018	0.988	70.00%	5.00%	5.00%	15.00%	5.00%
	2019	0.991	70.00%	5.00%	5.00%	15.00%	5.00%
	2020	0.996	10.00%	5.00%	5.00%	5.00%	75.00%
	2021	1.000	49.03%	35.97%	5.00%	5.00%	5.00%

Appendix to Chapter 6

C.1 Composite indicators (CIs) and categories for all wholesale water utilities in each year

Table C.1: CIs and categories for all wholesale water utilities in each year

Year	Company ID	Company	Category	Deterministic CI		Robust CI		Robust Conditional CI	
				RISI	AMMI	RISI	AMMI	RISI	AMMI
2016	A1	Águas de Santo André	Soldier	0.713	0.764	0.732	0.770	0.918	0.823
	A2	Águas do Algarve	Star	0.854	0.978	0.883	0.979	0.928	0.998
	A4	Águas do Centro Litoral	Infant	0.724	0.735	0.750	0.740	0.771	0.750
	A5	Águas do Norte	Infant	0.823	0.841	0.846	0.848	0.888	0.880
	A6	Águas do Vale do Tejo	Soldier	0.803	0.851	0.836	0.852	1.001	0.868
	A7	Águas do Vouga	Infant	0.823	0.602	0.853	0.606	0.893	0.615
	A8	Águas Públicas do Alentejo	Infant	0.754	0.709	0.818	0.714	0.754	0.842
	A9	EPAL	Learner	0.764	0.993	0.788	0.996	0.911	0.999
	A10	ICOVI	Infant	0.665	0.670	0.686	0.676	0.667	0.794
2017	A1	Águas de Santo André	Infant	0.653	0.764	0.663	0.770	0.765	0.822
	A2	Águas do Algarve	Star	0.858	0.978	0.887	0.979	0.933	0.998
	A3	Águas do Douro e Paiva	Star	0.811	0.891	0.840	0.898	0.974	0.917
	A4	Águas do Centro Litoral	Learner	0.775	0.918	0.794	0.925	0.826	0.937
	A5	Águas do Norte	Star	0.874	0.935	0.908	0.942	0.987	0.954
	A6	Águas do Vale do Tejo	Soldier	0.801	0.859	0.838	0.860	1.009	0.876
	A7	Águas do Vouga	Infant	0.821	0.708	0.855	0.708	0.885	0.722
	A8	Águas Públicas do Alentejo	Infant	0.772	0.734	0.831	0.739	0.773	0.872
	A9	EPAL	Star	0.787	0.993	0.824	0.996	0.956	0.999
	A10	ICOVI	Infant	0.877	0.703	0.936	0.709	0.877	0.835
2018	A1	Águas de Santo André	Infant	0.659	0.764	0.671	0.770	0.790	0.822
	A2	Águas do Algarve	Star	0.865	0.978	0.904	0.979	0.950	0.998
	A3	Águas do Douro e Paiva	Star	0.793	1.000	0.820	1.000	0.938	1.000
	A4	Águas do Centro Litoral	Infant	0.769	0.881	0.788	0.887	0.819	0.898
	A5	Águas do Norte	Learner	0.816	0.935	0.843	0.942	0.908	0.954
	A6	Águas do Vale do Tejo	Infant	0.776	0.860	0.799	0.860	0.855	0.884
	A7	Águas do Vouga	Infant	0.861	0.866	0.928	0.873	0.913	0.887
	A8	Águas Públicas do Alentejo	Soldier	0.939	0.738	0.988	0.744	0.940	0.876
	A9	EPAL	Star	0.791	0.993	0.827	0.996	0.960	0.999
	A10	ICOVI	Learner	0.695	0.760	0.752	0.765	0.734	0.902
2019	A1	Águas de Santo André	Infant	0.637	0.802	0.646	0.808	0.733	0.863
	A2	Águas do Algarve	Star	0.880	0.979	0.914	0.980	0.995	0.999
	A3	Águas do Douro e Paiva	Star	0.809	1.000	0.832	1.000	0.942	1.000
	A4	Águas do Centro Litoral	Learner	0.788	0.904	0.810	0.911	0.842	0.923
	A5	Águas do Norte	Star	0.826	0.981	0.855	0.988	0.939	1.000
	A6	Águas do Vale do Tejo	Infant	0.778	0.862	0.799	0.863	0.863	0.894
	A7	Águas do Vouga	Soldier	0.880	0.867	0.947	0.875	0.922	0.894
	A8	Águas Públicas do Alentejo	Soldier	1.000	0.738	1.046	0.744	1.001	0.879
	A9	EPAL	Star	0.799	0.993	0.834	0.996	0.963	0.999
	A10	ICOVI	Learner	0.786	0.801	0.871	0.808	0.833	0.949
2020	A1	Águas de Santo André	Infant	0.660	0.825	0.672	0.832	0.833	0.885
	A2	Águas do Algarve	Star	0.898	0.979	0.932	0.980	1.002	0.999
	A3	Águas do Douro e Paiva	Star	0.801	1.000	0.823	1.000	0.929	1.000
	A4	Águas do Centro Litoral	Learner	0.778	0.896	0.799	0.902	0.831	0.914
	A5	Águas do Norte	Star	0.811	0.981	0.839	0.988	0.922	1.000
	A6	Águas do Vale do Tejo	Soldier	0.801	0.862	0.836	0.863	0.997	0.894
	A7	Águas do Vouga	Star	1.000	0.869	1.138	0.876	1.057	0.901
	A8	Águas Públicas do Alentejo	Infant	0.818	0.724	0.850	0.730	0.819	0.861
	A9	EPAL	Star	0.775	1.000	0.807	1.004	0.932	1.000
	A10	ICOVI	Infant	0.710	0.703	0.776	0.709	0.767	0.836

Appendix to Chapter 7

D.1 Composite indicators (CIs) for all retail water utilities in 2020

Table D.1: CIs and categories for all retail water utilities in 2020.

Utility ID	Utility	Category	Deterministic CI		Robust CI		Robust Conditional CI	
			RISI	AMMI	RISI	AMMI	RISI	AMMI
B1	AGERE	STAR	0.961	0.895	1.004	0.896	0.997	0.897
B2	Águas da Azambuja	LEARNER	0.665	0.705	0.694	0.709	0.849	0.997
B3	Águas da Covilhã	STAR	0.735	0.715	0.771	0.716	0.909	0.743
B4	Águas da Figueira	STAR	0.938	1.000	1.018	1.002	1.000	1.000
B5	Águas da Região de Aveiro	STAR	0.706	0.930	0.761	0.931	0.866	0.939
B6	Águas da Teja	STAR	0.767	0.730	0.922	0.731	0.998	0.817
B7	Águas de Alenquer	LEARNER	0.792	0.980	0.831	0.985	0.836	1.000
B8	Águas de Barcelos	LEARNER	0.607	0.980	0.819	0.982	0.850	0.980
B9	Águas de Carrazeda	STAR	0.825	0.675	0.846	0.675	0.993	0.743
B10	Águas de Cascais	LEARNER	0.747	0.990	0.772	0.994	0.854	0.995
B11	Águas de Coimbra	STAR	0.824	0.955	1.013	0.956	1.000	0.970
B12	Águas de Gaia	LEARNER	0.730	0.885	0.741	0.886	0.737	0.887
B13	Águas de Gondomar	STAR	1.000	1.000	1.051	1.003	1.000	1.000
B14	Águas de Ourém	STAR	0.839	0.850	0.876	0.851	0.911	0.850
B15	Águas de Paços de Ferreira	STAR	0.751	0.825	0.948	0.833	0.999	0.839
B16	Águas de Paredes	STAR	1.000	0.975	1.276	0.976	1.000	0.975
B17	Águas de S. João	INFANT	0.750	0.580	0.768	0.580	0.790	0.593
B18	Águas de Santarém	STAR	0.797	0.955	0.833	0.960	0.976	0.998
B19	Águas de Santo André	STAR	1.000	0.820	1.012	0.821	1.000	0.904
B20	Águas de Valongo	STAR	0.747	0.975	0.818	0.976	0.868	0.975
B21	Águas de Vila Real de Santo António	LEARNER	0.629	0.865	0.670	0.866	0.717	0.865
B22	Águas do Alto Minho	STAR	0.590	0.715	0.661	0.716	0.976	0.746
B23	Águas do Baixo Mondego e Gândara	LEARNER	0.539	0.720	0.563	0.721	0.664	0.745
B24	Águas do Interior - Norte	SOLDIER	0.699	0.660	0.751	0.661	0.873	0.688
B25	Águas do Lena	STAR	0.785	0.845	0.872	0.846	0.997	0.995
B26	Águas do Marco	INFANT	0.536	0.735	0.591	0.736	0.797	0.735
B27	Águas do Norte	LEARNER	0.537	0.770	0.569	0.771	0.713	0.825
B28	Águas do Planalto	STAR	1.000	0.920	1.057	0.925	1.000	0.927
B29	Águas do Porto	STAR	1.000	0.985	1.038	0.986	1.000	0.987
B30	Águas do Ribatejo	STAR	0.818	0.740	0.844	0.741	0.956	0.768
B31	Águas do Sado	STAR	0.797	0.950	0.820	0.956	0.896	0.956
B32	AMBIOLHÃO	INFANT	0.638	0.665	0.646	0.665	0.678	0.675
B33	Aquaervas	SOLDIER	0.768	0.470	0.782	0.470	0.976	0.517
B34	Aquafundalia	SOLDIER	0.642	0.440	0.731	0.440	0.972	0.492
B35	Aquamaior	STAR	0.767	0.815	0.811	0.816	0.988	0.896
B36	Aquanena	STAR	0.814	0.870	0.879	0.871	0.969	0.922
B37	CARTÁGUA	INFANT	0.532	0.555	0.546	0.555	0.715	0.589
B38	CM de Aguiar da Beira	INFANT	0.534	0.375	0.550	0.375	0.613	0.422
B39	CM de Alandroal	LEARNER	0.573	0.840	0.640	0.841	0.811	0.963
B40	CM de Albufeira	LEARNER	0.533	0.805	0.569	0.810	0.734	0.961
B41	CM de Alcácer do Sal	INFANT	0.547	0.425	0.590	0.425	0.636	0.448
B42	CM de Alcochete	INFANT	0.699	0.480	0.708	0.480	0.746	0.555
B43	CM de Alcoutim	STAR	0.637	0.765	0.786	0.766	0.984	0.824
B44	CM de Alfândega da Fé	STAR	0.620	0.990	0.652	0.991	0.872	1.001
B45	CM de Alijó	INFANT	0.532	0.265	0.559	0.265	0.534	0.271

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Utility ID	Utility	Category	Deterministic CI		Robust CI		Robust Conditional CI	
			RISI	AMMI	RISI	AMMI	RISI	AMMI
B46	CM de Aljezur	INFANT	0.532	0.445	0.575	0.445	0.652	0.495
B47	CM de Aljustrel	LEARNER	0.547	0.780	0.564	0.781	0.600	0.822
B48	CM de Almeida	INFANT	0.535	0.465	0.672	0.465	0.631	0.522
B49	CM de Almodôvar	SOLDIER	0.632	0.595	0.725	0.595	0.955	0.668
B50	CM de Alter do Chão	INFANT	0.554	0.295	0.613	0.295	0.791	0.331
B51	CM de Alvito	LEARNER	0.539	0.730	0.586	0.731	0.700	0.820
B52	CM de Amares	SOLDIER	0.924	0.625	1.024	0.626	0.995	0.636
B53	CM de Anadia	INFANT	0.533	0.510	0.539	0.510	0.560	0.547
B54	CM de Arganil	LEARNER	0.787	0.715	0.799	0.716	0.826	0.868
B55	CM de Armamar	INFANT	0.532	0.510	0.555	0.510	0.648	0.518
B56	CM de Arraiolos	INFANT	0.532	0.455	0.582	0.455	0.746	0.510
B57	CM de Arronches	INFANT	0.532	0.245	0.552	0.245	0.667	0.275
B58	CM de Arruda dos Vinhos	LEARNER	0.638	0.840	0.644	0.841	0.676	0.916
B59	CM de Avis	SOLDIER	0.539	0.465	0.643	0.465	0.924	0.522
B60	CM de Barrancos	SOLDIER	1.000	0.495	1.114	0.495	1.009	0.556
B61	CM de Barreiro	STAR	0.787	1.000	0.839	1.000	0.971	1.000
B62	CM de Belmonte	INFANT	0.532	0.535	0.537	0.535	0.576	0.601
B63	CM de Bombarral	STAR	0.878	0.930	0.996	0.931	1.005	0.996
B64	CM de Borba	INFANT	0.535	0.455	0.551	0.455	0.576	0.575
B65	CM de Boticas	SOLDIER	1.000	0.585	1.064	0.586	1.002	0.594
B66	CM de Bragança	STAR	0.849	1.000	0.959	1.002	0.977	1.000
B67	CM de Cadaval	LEARNER	0.533	0.790	0.558	0.791	0.636	0.995
B68	CM de Castelo de Paiva	INFANT	0.533	0.350	0.548	0.350	0.558	0.357
B69	CM de Castelo de Vide	INFANT	0.548	0.330	0.587	0.330	0.634	0.371
B70	CM de Castro Daire	INFANT	0.529	0.365	0.532	0.367	0.542	0.595
B71	CM de Castro Marim	INFANT	0.557	0.575	0.711	0.576	0.822	0.635
B72	CM de Castro Verde	INFANT	0.534	0.495	0.580	0.495	0.580	0.522
B73	CM de Celorico da Beira	INFANT	0.532	0.465	0.575	0.465	0.611	0.521
B74	CM de Chaves	LEARNER	0.575	0.855	0.586	0.856	0.651	0.918
B75	CM de Condeixa-a-Nova	SOLDIER	1.000	0.555	1.036	0.556	1.003	0.595
B76	CM de Constância	LEARNER	0.532	0.680	0.569	0.681	0.611	0.762
B77	CM de Crato	INFANT	0.532	0.460	0.552	0.460	0.604	0.516
B78	CM de Cuba	SOLDIER	0.539	0.550	0.637	0.550	0.872	0.617
B79	CM de Entroncamento	LEARNER	0.532	0.710	0.552	0.711	0.664	0.846
B80	CM de Espinho	LEARNER	0.684	0.775	0.692	0.777	0.856	0.902
B81	CM de Estremoz	SOLDIER	0.727	0.700	0.735	0.701	0.881	0.738
B82	CM de Évora	INFANT	0.601	0.360	0.721	0.360	0.653	0.376
B83	CM de Felgueiras	INFANT	0.700	0.595	0.725	0.595	0.774	0.598
B84	CM de Ferreira do Alentejo	STAR	0.722	0.885	0.777	0.886	0.957	0.934
B85	CM de Figueira de Castelo Rodrigo	INFANT	0.622	0.660	0.648	0.661	0.842	0.739
B86	CM de Fornos de Algodres	LEARNER	0.539	0.695	0.617	0.696	0.667	0.968
B87	CM de Fronteira	INFANT	0.532	0.560	0.552	0.560	0.584	0.628
B88	CM de Gavião	STAR	0.533	0.700	0.592	0.701	0.919	0.786
B89	CM de Golegã	INFANT	0.688	0.425	0.703	0.425	0.803	0.477
B90	CM de Gouveia	INFANT	0.532	0.260	0.564	0.260	0.674	0.279
B91	CM de Grândola	STAR	0.604	0.930	0.874	0.931	0.980	0.981
B92	CM de Guarda	INFANT	0.532	0.395	0.552	0.395	0.572	0.419
B93	CM de Lagoa	INFANT	0.533	0.620	0.550	0.621	0.644	0.656
B94	CM de Lagos	SOLDIER	0.818	0.595	0.839	0.596	0.919	0.629
B95	CM de Lamego	INFANT	0.532	0.405	0.569	0.405	0.766	0.434
B96	CM de Loulé	INFANT	0.531	0.445	0.540	0.445	0.570	0.472
B97	CM de Lourinhã	LEARNER	0.532	0.785	0.582	0.786	0.646	0.842
B98	CM de Lousada	SOLDIER	1.000	0.165	1.079	0.165	1.000	0.177
B99	CM de Macedo de Cavaleiros	LEARNER	0.740	0.820	0.748	0.821	0.800	0.833
B100	CM de Mangualde	STAR	0.713	0.755	1.131	0.756	0.999	0.810

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Utility ID	Utility	Category	Deterministic CI		Robust CI		Robust Conditional CI	
			RISI	AMMI	RISI	AMMI	RISI	AMMI
B101	CM de Manteigas	INFANT	0.530	0.505	0.534	0.505	0.547	0.568
B102	CM de Marinha Grande	STAR	0.761	0.880	0.825	0.881	0.996	0.934
B103	CM de Marvão	LEARNER	0.530	0.375	0.535	0.377	0.571	0.986
B104	CM de Mealhada	SOLDIER	0.616	0.595	0.688	0.596	0.894	0.702
B105	CM de Mêda	INFANT	0.603	0.415	0.672	0.415	0.765	0.467
B106	CM de Melgaço	STAR	0.927	0.820	1.039	0.821	1.000	0.833
B107	CM de Mértola	LEARNER	0.656	0.655	0.821	0.655	0.821	0.779
B108	CM de Miranda do Corvo	SOLDIER	0.754	0.490	0.861	0.490	0.994	0.525
B109	CM de Miranda do Douro	INFANT	0.532	0.580	0.556	0.580	0.537	0.589
B110	CM de Mirandela	INFANT	0.532	0.525	0.549	0.525	0.535	0.534
B111	CM de Mogadouro	SOLDIER	1.000	0.430	1.060	0.430	1.001	0.438
B112	CM de Moimenta da Beira	INFANT	0.590	0.260	0.593	0.260	0.605	0.265
B113	CM de Moita	INFANT	0.614	0.680	0.630	0.681	0.848	0.680
B114	CM de Monção	INFANT	0.723	0.575	0.734	0.575	0.778	0.586
B115	CM de Mondim de Basto	SOLDIER	0.855	0.265	1.093	0.265	1.004	0.271
B116	CM de Monforte	INFANT	0.529	0.395	0.530	0.395	0.541	0.443
B117	CM de Montalegre	SOLDIER	0.615	0.215	0.661	0.215	0.914	0.222
B118	CM de Montemor-o-Novo	STAR	0.763	0.750	0.796	0.751	0.975	0.790
B119	CM de Mora	STAR	1.000	0.815	1.090	0.816	1.014	0.996
B120	CM de Moura	INFANT	0.531	0.510	0.537	0.510	0.556	0.537
B121	CM de Mourão	INFANT	0.532	0.635	0.548	0.636	0.606	0.719
B122	CM de Nelas	LEARNER	0.566	0.830	0.587	0.831	0.657	0.890
B123	CM de Nisa	SOLDIER	0.926	0.225	1.029	0.225	1.010	0.252
B124	CM de Óbidos	INFANT	0.532	0.650	0.558	0.650	0.599	0.697
B125	CM de Odemira	LEARNER	0.590	0.945	0.614	0.946	0.674	0.999
B126	CM de Oleiros	LEARNER	0.590	0.755	0.675	0.756	0.800	0.846
B127	CM de Oliveira de Frades	SOLDIER	0.845	0.640	0.868	0.641	1.001	0.717
B128	CM de Oliveira do Hospital	SOLDIER	0.535	0.630	0.596	0.631	0.886	0.676
B129	CM de Ourique	LEARNER	0.576	0.860	0.610	0.861	0.716	0.964
B130	CM de Palmela	LEARNER	0.769	0.635	0.792	0.636	0.821	0.776
B131	CM de Penalva do Castelo	INFANT	0.532	0.370	0.568	0.370	0.592	0.415
B132	CM de Penamacor	INFANT	0.532	0.555	0.554	0.555	0.602	0.622
B133	CM de Penedono	SOLDIER	0.776	0.280	0.791	0.280	0.969	0.287
B134	CM de Pinhel	INFANT	0.553	0.465	0.590	0.465	0.690	0.499
B135	CM de Pombal	STAR	0.867	0.895	0.891	0.896	0.942	0.960
B136	CM de Ponte da Barca	SOLDIER	0.658	0.730	0.748	0.731	0.883	0.741
B137	CM de Ponte de Sor	SOLDIER	1.000	0.590	1.084	0.590	1.001	0.622
B138	CM de Portel	INFANT	0.532	0.555	0.559	0.555	0.669	0.623
B139	CM de Porto de Mós	INFANT	0.683	0.570	0.738	0.570	0.816	0.611
B140	CM de Póvoa de Lanhoso	LEARNER	0.629	0.910	0.951	0.911	0.803	0.924
B141	CM de Póvoa de Varzim	INFANT	0.535	0.525	0.592	0.525	0.723	0.525
B142	CM de Proença-a-Nova	SOLDIER	0.578	0.415	0.830	0.415	0.960	0.447
B143	CM de Redondo	LEARNER	0.547	0.875	0.587	0.876	0.638	0.982
B144	CM de Reguengos de Monsaraz	STAR	0.666	0.780	0.994	0.781	0.991	0.822
B145	CM de Resende	INFANT	0.532	0.325	0.549	0.325	0.621	0.333
B146	CM de Ribeira de Pena	SOLDIER	0.723	0.610	0.831	0.611	0.950	0.620
B147	CM de Rio Maior	INFANT	0.532	0.630	0.556	0.631	0.579	0.666
B148	CM de Sabugal	INFANT	0.531	0.335	0.538	0.335	0.592	0.422
B149	CM de Santiago do Cacém	SOLDIER	1.000	0.610	1.192	0.611	1.000	0.637
B150	CM de São Brás de Alportel	STAR	0.740	0.785	0.749	0.786	0.879	0.853
B151	CM de São João da Pesqueira	INFANT	0.537	0.585	0.597	0.585	0.813	0.594
B152	CM de São Pedro do Sul	INFANT	0.669	0.590	0.679	0.591	0.785	0.632
B153	CM de Sátão	STAR	0.735	0.880	0.811	0.881	0.999	0.985
B154	CM de Seia	INFANT	0.653	0.645	0.756	0.645	0.820	0.691
B155	CM de Seixal	INFANT	0.540	0.615	0.563	0.616	0.709	0.615
B156	CM de Sernancelhe	SOLDIER	0.650	0.315	0.672	0.315	0.908	0.323
B157	CM de Serpa	LEARNER	0.534	0.840	0.585	0.841	0.594	0.956
B158	CM de Sertão	INFANT	0.532	0.650	0.558	0.651	0.598	0.697
B159	CM de Sesimbra	SOLDIER	0.888	0.665	0.969	0.666	1.000	0.737
B160	CM de Silves	INFANT	0.655	0.675	0.666	0.676	0.750	0.700
B161	CM de Sines	STAR	0.872	0.765	0.902	0.766	0.999	0.836
B162	CM de Sobral de Monte Agraço	INFANT	0.532	0.545	0.553	0.545	0.623	0.584
B163	CM de Sousel	SOLDIER	1.000	0.555	1.088	0.555	1.076	0.623

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Utility ID	Utility	Category	Deterministic CI		Robust CI		Robust Conditional CI	
			RISI	AMMI	RISI	AMMI	RISI	AMMI
B164	CM de Tábuia	SOLDIER	1.000	0.315	1.464	0.315	1.012	0.355
B165	CM de Tabuaço	SOLDIER	1.000	0.145	1.211	0.145	1.005	0.148
B166	CM de Tarouca	LEARNER	0.529	0.705	0.534	0.709	0.568	0.964
B167	CM de Terras de Bouro	INFANT	0.538	0.360	0.561	0.360	0.615	0.367
B168	CM de Vale de Cambra	STAR	1.000	0.985	2.082	0.986	1.024	0.999
B169	CM de Valpaços	STAR	1.000	0.600	1.279	0.601	1.003	0.925
B170	CM de Vendas Novas	LEARNER	0.532	0.715	0.556	0.716	0.568	0.851
B171	CM de Viana do Alentejo	STAR	0.853	0.830	0.982	0.831	0.915	0.931
B172	CM de Vidigueira	LEARNER	0.532	0.670	0.618	0.671	0.782	0.752
B173	CM de Vieira do Minho	INFANT	0.533	0.715	0.606	0.716	0.702	0.725
B174	CM de Vila de Rei	STAR	1.000	0.680	1.316	0.681	1.002	0.762
B175	CM de Vila do Bispo	INFANT	0.531	0.435	0.541	0.435	0.573	0.489
B176	CM de Vila Flor	INFANT	0.539	0.625	0.547	0.625	0.612	0.634
B177	CM de Vila Nova de Cerveira	SOLDIER	1.000	0.705	1.114	0.706	1.000	0.714
B178	CM de Vila Nova de Famalicão	INFANT	0.682	0.650	0.691	0.651	0.727	0.654
B179	CM de Vila Nova de Foz Coa	INFANT	0.532	0.315	0.562	0.315	0.536	0.321
B180	CM de Vila Pouca de Aguiar	INFANT	0.530	0.565	0.533	0.565	0.533	0.575
B181	CM de Vila Velha de Ródão	INFANT	0.560	0.575	0.603	0.575	0.685	0.644
B182	CM de Vila Verde	STAR	0.763	0.765	0.784	0.769	0.861	0.765
B183	CM de Vimioso	SOLDIER	0.740	0.645	0.754	0.646	0.939	0.654
B184	CM de Vinhais	SOLDIER	1.000	0.405	1.082	0.405	1.000	0.414
B185	CM de Vouzela	LEARNER	0.534	0.705	0.564	0.706	0.561	0.790
B186	EMAR de Portimão	STAR	0.743	0.800	0.775	0.801	0.887	0.812
B187	EMAS de Beja	STAR	0.805	0.985	0.879	0.986	0.934	1.000
B188	EPAL	STAR	0.973	0.990	0.997	0.999	1.000	1.000
B189	Esposende Ambiente	STAR	0.539	0.905	0.683	0.906	0.903	0.910
B190	FAGAR - Faro	STAR	0.821	0.925	0.844	0.930	0.930	0.993
B191	Indaqua Fafe	LEARNER	0.535	1.000	0.589	1.001	0.828	1.000
B192	Indaqua Feira	STAR	0.832	1.000	1.008	1.001	1.000	1.000
B193	Indaqua Matosinhos	STAR	1.000	1.000	1.027	1.005	1.000	1.000
B194	Indaqua Oliveira de Azeméis	STAR	0.728	0.970	0.784	0.979	0.956	0.987
B195	Indaqua Santo Tirso/Trofa	STAR	0.645	1.000	0.984	1.001	1.000	1.000
B196	Indaqua Vila do Conde	STAR	0.835	1.000	0.996	1.001	1.000	1.000
B197	INFRALOBO	SOLDIER	0.758	0.635	0.878	0.636	0.925	0.648
B198	INFRAMOURA	STAR	0.872	0.980	0.911	0.981	0.999	0.995
B199	INFRAQUINTA	STAR	1.000	0.985	1.106	0.986	1.000	1.000
B200	INFRATRÓIA	SOLDIER	0.778	0.515	0.796	0.515	0.963	0.528
B201	INOVA	STAR	1.000	1.000	1.103	1.003	1.000	1.000
B202	Penafiel Verde	STAR	0.855	0.870	0.896	0.871	0.979	0.875
B203	SIMAR de Loures e Odivelas	STAR	0.787	0.835	0.822	0.836	0.946	0.835
B204	SIMAS de Oeiras e Amadora	STAR	0.818	0.945	0.936	0.947	1.000	0.979
B205	SM de Abrantes	STAR	0.907	0.915	1.004	0.916	1.000	0.972
B206	SM de Alcobaça	INFANT	0.646	0.425	0.690	0.426	0.776	0.521
B207	SM de Castelo Branco	STAR	0.943	0.910	1.074	0.911	1.000	0.971
B208	SM de Nazaré	LEARNER	0.645	0.770	0.654	0.771	0.695	0.839
B209	SMAS de Almada	STAR	0.787	0.885	0.798	0.887	0.920	0.929
B210	SMAS de Caldas da Rainha	STAR	0.710	0.800	0.757	0.801	0.882	0.849
B211	SMAS de Leiria	SOLDIER	0.820	0.585	0.839	0.585	0.920	0.620
B212	SMAS de Mafra	STAR	0.941	0.835	0.990	0.836	1.000	0.936
B213	SMAS de Montijo	SOLDIER	0.927	0.460	0.978	0.460	1.000	0.510
B214	SMAS de Peniche	LEARNER	0.639	0.770	0.716	0.771	0.821	0.818
B215	SMAS de Sintra	STAR	0.743	0.795	0.772	0.796	0.985	0.795
B216	SMAS de Torres Vedras	LEARNER	0.746	0.700	0.768	0.701	0.799	0.743
B217	SMAS de Vila Franca de Xira	LEARNER	0.787	0.730	0.820	0.731	0.853	0.807
B218	SMAS de Viseu	SOLDIER	0.818	0.530	0.886	0.530	0.896	0.562
B219	SMAT de Portalegre	SOLDIER	0.604	0.395	0.680	0.395	0.954	0.427
B220	SMEAS de Maia	STAR	0.571	0.745	0.628	0.746	0.926	0.746
B221	Taviraverde	STAR	0.675	0.975	0.725	0.979	0.897	1.000
B222	Tejo Ambiente	INFANT	0.532	0.610	0.547	0.610	0.597	0.631
B223	VIMÁGUA	STAR	0.874	0.845	0.904	0.849	0.979	0.874

Appendix to Chapter 8

E.1 Linearisation of the equation to determine the individual assets' IVI

This section details the steps needed to convert equation (8.11) in linear constraints for the optimisation model described in item 8.3.2.2.

$$IVI_{it}(x_{ipt}) = \frac{rl_{i0}^{adj} - t + \sum_{j=1}^t \sum_{p=1}^{P_t} \Delta_{ip} \times x_{ipj}}{rl_{i0}^{adj} + a_{i0} + \sum_{j=1}^t \sum_{p=1}^{P_t} \Delta_{ip} \times x_{ipj}}$$

Two auxiliary decision variables, k_{it} and y_{ipt} , are employed for the linearisation, according to equations (E.1) and (E.2).

$$k_{it} = \frac{1}{rl_{i0}^{adj} + a_{i0} + \sum_{j=1}^t \sum_{p=1}^{P_t} \Delta_{ip} \times x_{ipj}} \quad (\text{E.1})$$

$$y_{ipt} = k_{it} \times x_{ipt}. \quad (\text{E.2})$$

Therefore, equation (8.11) can be rewritten as:

$$IVI_{it}(x_{ipt}) = k_{it} \times (rl_{i0}^{adj} - t + \sum_{j=1}^t \sum_{p=1}^{P_t} \Delta_{ip} \times x_{ipj}). \quad (\text{E.3})$$

By replacing the new variables (k_{it} and y_{ipt}) in (E.3), we obtain the linear equation (E.4). This equation defines IVI_{it} in function of the new decision variables k_{it} and y_{ipt} .

$$IVI_{it}(k_{it}, y_{ipt}) = (rl_{i0}^{adj} - t) \times k_{it} + \sum_{j=1}^t \sum_{p=1}^{P_t} \Delta_{ip} \times y_{ipj}, \quad \forall i \in \{1, 2, \dots, N\}, \forall t \in \{1, 2, \dots, T\} \quad (\text{E.4})$$

The constraints (E.5) are derived from expression (E.1), and the constraints (E.6), (E.7) and (E.8) are obtained from (E.2). Expressions (E.6), (E.7) and (E.8) associate the binary variables x_{ipt} with the variables y_{ipt} and k_{ip} . The constant M is a large integer number.

$$(rl_{i0}^{adj} + a_{i0}) \times k_{it} + \sum_{j=1}^t \sum_{p=1}^{P_t} \Delta_{ip} \times y_{ipj} = 1, \quad \forall i \in \{1, 2, \dots, N\}, \forall t \in \{1, 2, \dots, T\} \quad (\text{E.5})$$

$$y_{ipt} \leq k_{it}, \quad \forall i \in \{1, 2, \dots, N\}, \forall p \in \{1, 2, \dots, P_i\}, \forall t \in \{1, 2, \dots, T\} \quad (\text{E.6})$$

$$y_{ipt} \leq Mx_{ipt}, \quad \forall i \in \{1, 2, \dots, N\}, \forall p \in \{1, 2, \dots, P_i\}, \forall t \in \{1, 2, \dots, T\} \quad (\text{E.7})$$

$$y_{ipt} \geq k_{it} - M(1 - x_{ipt}), \quad \forall i \in \{1, 2, \dots, N\}, \forall p \in \{1, 2, \dots, P_i\}, \forall t \in \{1, 2, \dots, T\} \quad (\text{E.8})$$

E.2 Jovim Pumping Station asset data before the planning period

Table E.1: Asset data for t_0 - Jovim PS Infrastructure

Asset	Replacement	Adjusted	Adjusted	Current	IVI_{i0}
	Cost	residual life	useful life	Value	
	rc_{i0}	rl_{i0}^{adj}	ul_{i0}^{adj}	cv_{i0}	
	(€)	(years)	(years)	(€)	%
1	645,000	41.7	63.7	422,368	65.5
2	645,000	32.7	54.7	385,511	59.8
3	250,000	7.9	29.9	65,878	26.4
4	250,000	8.5	30.5	69,644	27.9
5	224,000	9.1	31.1	65,659	29.3
6	280,000	9.4	31.4	84,060	30.0
7	20,000	13.9	34.9	7,959	39.8
8	100,000	12.7	21.7	58,480	58.5
9	180,000	14.5	33.5	77,967	43.3
10	180,000	14.5	33.5	77,967	43.3
11	180,000	14.5	33.5	77,967	43.3
12	180,000	14.5	33.5	77,967	43.3
13	285,312	14.7	35.7	117,428	41.2
14	285,312	11.5	32.7	100,768	35.3
15	285,312	14.7	35.7	117,428	41.2
16	285,312	11.5	32.5	100,768	35.3
17	20,000	9.1	31.1	5,862	29.3
18	20,000	10.4	32.4	6,417	32.1
19	56,388	32.2	41.2	44,067	78.1
20	56,388	32.2	41.2	44,067	78.1
21	88,917	32.8	41.8	69,767	78.5

E.3 Alternative project plans from multi-objective optimisation

Table E.2: Selected projects for each year of the planning horizon (t_1 to t_5) from Multi-objective Optimisation

Asset	Plan A				Plan B				Plan C				Plan D			
Group	Project	Year	Project	Year	Project	Year	Project	Year	Project	Year	Project	Year	Project	Year	Project	Year
Civil work	P _{1a}	-	P _{1b}	-	P _{1a}	-	P _{1b}	-	P _{1a}	-	P _{1b}	-	P _{1a}	-	P _{1b}	-
	P _{2a}	-	P _{2b}	-	P _{2a}	-	P _{2b}	-	P _{2a}	-	P _{2b}	-	P _{2a}	-	P _{2b}	-
Electrical facilities	P _{3a}	t_4	P _{3b}	-	P _{3a}	t_4	P _{3b}	-	P _{3a}	t_4	P _{3b}	-	P _{3a}	t_4	P _{3b}	-
	P _{4a}	t_5	P _{4b}	-	P _{4a}	-	P _{4b}	t_2	P _{4a}	-	P _{4b}	-	P _{4a}	t_5	P _{4b}	-
	P _{5a}	-	P _{5b}	-	P _{5a}	t_2	P _{5b}	-	P _{5a}	-	P _{5b}	-	P _{5a}	-	P _{5b}	t_2
	P _{6a}	t_2	P _{6b}	-	P _{6a}	t_1	P _{6b}	-	P _{6a}	t_2	P _{6b}	-	P _{6a}	t_2	P _{6b}	-
Equipment	P _{7a}	t_5	P _{7b}	-	P _{7a}	-	P _{7b}	t_5	P _{7a}	t_2	P _{7b}	-	P _{7a}	t_4	P _{7b}	-
	P _{8a}	-	P _{8b}	t_2	P _{8a}	-	P _{8b}	t_3	P _{8a}	t_2	P _{8b}	-	P _{8a}	t_5	P _{8b}	-
	P _{9a}	t_1	P _{9b}	t_3	P _{9a}	-	P _{9b}	-	P _{9a}	t_2	P _{9b}	t_1	P _{9a}	t_3	P _{9b}	t_4
	P _{10a}	t_4	P _{10b}	-	P _{10a}	t_4	P _{10b}	t_3	P _{10a}	t_4	P _{10b}	t_2	P _{10a}	t_4	P _{10b}	t_1
	P _{11a}	-	P _{11b}	-	P _{11a}	-	P _{11b}	t_1	P _{11a}	t_1	P _{11b}	-	P _{11a}	-	P _{11b}	t_1
	P _{12a}	t_1	P _{12b}	t_5	P _{12a}	-	P _{12b}	-	P _{12a}	t_3	P _{12b}	-	P _{12a}	t_3	P _{12b}	-
	P _{13a}	t_1	P _{13b}	t_1	P _{13a}	-	P _{13b}	t_1	P _{13a}	t_1	P _{13b}	t_1	P _{13a}	t_2	P _{13b}	t_1
	P _{14a}	-	P _{14b}	-	P _{14a}	-	P _{14b}	-	P _{14a}	t_1	P _{14b}	-	P _{14a}	t_1	P _{14b}	-
	P _{15a}	t_3	P _{15b}	t_2	P _{15a}	t_2	P _{15b}	t_5	P _{15a}	t_2	P _{15b}	t_5	P _{15a}	t_3	P _{15b}	-
	P _{16a}	t_2	P _{16b}	-	P _{16a}	-	P _{16b}	-	P _{16a}	t_3	P _{16b}	-	P _{16a}	-	P _{16b}	-
	P _{17a}	-	P _{17b}	-	P _{17a}	-	P _{17b}	t_3	P _{17a}	-	P _{17b}	-	P _{17a}	-	P _{17b}	-
	P _{18a}	-	P _{18b}	-	P _{18a}	-	P _{18b}	t_3	P _{18a}	-	P _{18b}	-	P _{18a}	-	P _{18b}	-
	P _{19a}	-	P _{19b}	-	P _{19a}	-	P _{19b}	t_5	P _{19a}	-	P _{19b}	t_5	P _{19a}	-	P _{19b}	t_5
	P _{20a}	t_1	P _{20b}	-	P _{20a}	-	P _{20b}	t_3	P _{20a}	-	P _{20b}	-	P _{20a}	-	P _{20b}	t_3
	P _{21a}	t_3	P _{21b}	-	P _{21a}	t_2	P _{21b}	-	P _{21a}	t_2	P _{21b}	-	P _{21a}	t_2	P _{21b}	-

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