Disaggregating for justice in a multi-purpose reservoir system

Finding the possibilities and limitations of objective disaggregation in an EMODPS model of the Zambezi River Basin

By

Roefs, W.S.

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Supervisor:	*Prof. dr. ir. Pieter van Gelder*	
Thesis committee:	*Dr. J. Zatarain Salazar,*	*TU Delft*
	D. Akoluk,	*TU Delft*

Code and data files are available at

https://github.com/poeufs/Zambezi-River-Basin-Multi-reservoir-EMODPS/tree/master

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ABBREVIATIONS

AI	Artificial Intelligence
DAF	Decision-Analytic Framework
DAFNE	Decision-Analytic Framework to explore the water-energy-food NExus
DP	Dynamic Programming
DPS	Direct Policy Search
EMODPS	Evolutionary Multi-Objective Direct Policy Search
EPA	Engineering and Policy Analysis
GBA	Generational Borg Algorithm
IAM	Integrated Assessment Model
MOEA	Multi-Objective Evolutionary Algorithm
MOO	Multi-Objective Optimization
SDP	Stochastic Dynamic Programming
WEF	Water, Energy, Food
ZRB	Zambezi River Basin

EXECUTIVE SUMMARY

The Zambezi River Basin (ZRB) is a critical resource for Southern Africa, supporting hydropower production, livelihoods, food security and ecosystems. With increasing freshwater scarcity and climate change induced droughts and floods in the ZRB, water allocation is increasingly critical, especially to those already carrying the burdens of climate change without reaping the profits of economic development. Effective management of this transboundary water system requires balancing competing objectives such as economic efficiency, social equity, and environmental sustainability.

In light of the DAFNE project, funded by the EU to create a Decision-Analytic Framework (DAF), an Evolutionary Multi Objective Direct Policy Search (EMODPS) framework was applied to the ZRB. EMODPS models combine Direct Policy Search (DPS) with Multi-Objective Evolutionary Algorithms (MOEA) to process complex simulations and continuously optimize for sequential decisions. The ZRB EMODPS model was created to identify the Pareto-optimal release policies for the five hydropower reservoirs and eight irrigation districts in the river basin (Zatarain Salazar & Sari, 2021). In the modelling process, there was a lack of consideration for distributive justice (Zatarain Salazar, 2023). In the baseline configuration, the five reservoirs were aggregated into one hydropower objective and the eight irrigation districts in the system were aggregated into one irrigation objective. The environmental flow at the Zambezi Delta constituted the third objective for the initial optimization.

This research disaggregates the hydropower and irrigation objectives to analyse what the effects are on the optimal release policies, particularly for smaller irrigation districts and reservoirs. The research question is: *How does the disaggregation of objectives influence the Pareto space for an EMODPS simulation-optimization model?* Four levels of aggregation were optimized: the baseline configuration with three objectives, the irrigation case with 11 objectives (including an individual objective for each irrigation district), the hydropower case with eight objectives (including the five hydropower reservoirs as objectives) and the full case with 16 objectives in total where the three baseline objectives are complemented with one objective for each irrigation district and hydropower reservoir. The Pareto set of the four different problem framings is visualized and analysed to conduct a comparison between the levels of aggregation.

Higher levels of aggregation may limit the insights provided by the Pareto front and increase the risk of further burdening marginalized groups. The initial hypothesis was that smaller irrigation districts and hydropower reservoirs would benefit from being considered as individual objectives. However, this hypothesis was not confirmed. The baseline aggregation of three objectives yielded better results for the total hydropower and irrigation deficits, even for the smaller districts and reservoirs.

The results reveal that disaggregation provides a more nuanced understanding of trade-offs but increases computational demands and complexity. The increased number of variables and constraints decreased the efficiency of the Generational Borg algorithm, making the study less feasible. Many-objective optimizations with more than 10 objectives pushed computational limits, displayed unexpected convergence behaviour, and posed challenges in presenting and interpreting large amounts of data. More sophisticated algorithms may better handle the consequences and limitations of objective aggregation in EMODPS models. This research highlights the trade-offs between equity and efficiency in water resource management and provides insights into the possibilities of disaggregating objectives for more just and precise policy-making.

The thesis fits into the Engineering and Policy Analysis curriculum due to its focus on international grand challenges, such as water resource allocation challenges and climate change consequences. The research applied multi-objective simulation-optimization modelling to support decision-making, data visualization and data analysis to consider the impact of modelling decisions on policy advice.

1 PROBLEM INTRODUCTION

The tension between nations and people over the use of water are increasing as climate change, growing economies and population growth put a strain on fresh water supplies (Giuliani et al., 2016). This growing demand for limited water resources is leading to conflicts and competition among various stakeholders. Transboundary water systems are complex multi-actor systems, and managing them involves balancing competing objectives such as flood security, economic efficiency, and environmental sustainability for different stakeholders within the same dynamic water system. Consequently, managing water resources effectively has become a critical challenge for policymakers, decision-makers and policy advisors alike. The uncertainties in these water systems are significant, and the stakes are high, as water can mean the difference between life and death. The survival threats posed by climate change and water scarcity will and has cause(d) violent conflicts in Southern Africa, and specifically in regions within the Zambezi River Basin (ZRB) (Swain et al., 2011).

The ZRB stretches out to eight countries: Angola, Botswana, Malawi, Mozambique, Namibia, Tanzania, Zambia and Zimbabwe. The basin was selected as one of two basins to be the focus of study for the DAFNE project, a four-year initiative funded by EU Horizon 2020 (Castelletti, 2019). The projects' main goal was to develop a Decision-Analytic Framework (DAF) for quantitative assessments of the Water, Energy and Food (WEF) nexus in complex and transboundary water resource systems in rapidly developing countries. Managing these systems involves navigating a multitude of variables and stakeholders, each with unique and often competing interests. The complexity of these transboundary water systems has led to an increase in the use of Artificial Intelligence (AI) to aid in decision-making processes (Giuliani et al., 2021; Kasprzyk et al., 2012; Reed et al., 2013).

Advanced AI techniques have been employed to provide more robust and efficient solutions for policies. One of the most prominent AI methodologies utilized in this context is simulation-based Multi-Objective Optimization (MOO). These optimization models are designed to capture the multifaceted nature of water systems, which includes their inherent complexity, dynamic behaviour, and the need to balance trade-offs between various objectives (Giuliani et al., 2016). For the ZRB, an Evolutionary Multi Objective Direct Policy Search (EMODPS) methodology was applied to optimize the release policies for multiple dams in the basin and the irrigation policies for several districts in the system (Zatarain Salazar & Sari, 2021). The goal of the optimization is to create release policies which balance water resource allocation between water, energy and food usage within the basin. One of the limitations of the created EMODPS model lies in its lack of consideration for distributive justice and the consequent use of high levels of aggregation (Zatarain Salazar, 2023).

As water management is becoming increasingly crucial, the importance of ethics and distributive justice is rising in this field. Policies which benefit a society on average over a period of time may have negative consequences to a certain group at a specific moment in time (Doorn, 2019). Often, marginalized and smaller communities are overlooked in making modelling decisions. The current simulation-optimization model of the Zambezi does not take distributive justice into account explicitly and it aggregates the irrigation districts and hydropower reservoirs without consideration for their size or the impact of these modelling decisions. Since this model is being used in the development of current and planned policies, it is essential to analyze the equitability of the policies which are optimized through EMODPS. The societal relevance of this research is to aid in creating more equitable policies and modelling practices. This relevance extends beyond the ZRB, as EMODPS is used in decision-making for water basins and systems globally (Giuliani et al., 2016) and distributive justice is often not explicitly considered (Reed et al., 2013). The focus on disaggregation as a method of increasing distributive justice in water resource planning and management is an even less well-researched topic with very limited literature on the matter (Kasprzyk et al., 2016).

This lack of explicitly accounting for distributive justice principles in the modelling process can be considered a systematic problem in research and practice concerning itself with simulation-optimization modelling (Yalew et al., 2021). During the modelling process, the modeler makes inherent assumptions, and during the decision-making process, policy makers make assumptions about what is considered the "best" outcome and which aggregations are acceptable. This oversight creates a significant risk, as these assumptions may neglect the needs of marginalized groups and fail to address issues of distributive justice. This challenge is further compounded by Arrow's paradox, also known as Arrow's impossibility theorem, which states that no rank-order voting system can meet a set of fairness criteria simultaneously when there are three or more options. The paradox highlights the inherent difficulties in achieving a perfectly fair and democratic decision-making process, as trade-offs and compromises are inevitable. Disaggregating objectives is an important method to battle Arrow's paradox (Kasprzyk et al., 2016). The scientific contribution of this research is to improve the validity of EMODPS by exploring the ways in which the disaggregation of objectives can add to the fairness of water allocation and management.

1.1 Existing knowledge

The existing knowledge that form the basis for this research can be divided into two main sections: optimization techniques and distributive justice.

1.1.1 Optimization

Optimization techniques are fundamental to addressing complex decision-making problems, enabling the identification of the most efficient solutions across multiple conflicting objectives through MOO.

Multi-Objective Optimization

MOO is applied in various fields, including politics, mechanics, and finance (Gunantara, 2018; Jafino et al., 2021). MOO involves optimizing for multiple objectives, with often conflicting desired outcomes. Multi-objective simulation-optimization frameworks have emerged as valuable strategies to find optimal solutions for resource allocation issues (Zatarain Salazar et al., 2016). MOEAs, MOO models which are similar to genetic algorithms, use dominance relationships in their optimization mechanism to select candidate solutions and allow estimations of the Pareto front in a single run (Giuliani et al., 2016; Reed et al., 2013). Due to the dynamic and stochastic factors that play a key role in multi-reservoir water systems, specific optimization techniques are required to capture the workings of the system. Direct Policy Search (DPS) is one such methodology that employs simulations to perform MOO for sequential decisions in a basin system. When DPS is combined with MOEAs, it results in Evolutionary Multi-Objective Direct Policy Search (EMODPS), providing a robust framework for designing adaptive operating policies.

Evolutionary Multi-Objective Direct Policy Search

EMODPS is a simulation-based optimization approach that integrates three core components to design Pareto approximate closed-loop operating policies for multi-purpose water reservoirs: 1) DPS for handling dynamic systems where decisions need to be made over time, 2) nonlinear approximating networks for modelling complex relationships and, 3) MOEAs for leveraging evolutionary techniques to efficiently explore and optimize multiple conflicting objectives (Giuliani et al., 2016). According to Giuliani et al. (2016) it is important that operating policies are adapted to the evolving system conditions, i.e. “closing the loop”. Dynamic planning frameworks like EMODPS allow for the revision of outcomes over time and are dependent on the characterization of uncertainties, making them useful in identifying and adapting to changing circumstances (Herman et al., 2020).

1.1.2 Distributive justice

Consequentialism, and utilitarianism specifically, is the most commonly used ethical paradigm in public policy because it aims to maximize overall 'good' and minimize 'bad' for everyone, regardless of their status (Doorn, 2019). However, this approach's disregard for the status quo can lead to an oversight of the unequal burdens and benefits of policy, potentially resulting in a lack of justice. An egalitarian approach, which emphasizes equal treatment and fairness, can lead to a more just allocation of resources. In the climate justice literature, justice often pertains to either distributive justice or procedural justice (Jafino et al., 2021). Distributive justice is concerned with the fair distribution of risks, benefits, resources, and goods across society (Doorn, 2019; Jafino et al., 2021). The focus of this research is on spatial intragenerational distributive justice. In the context of the ZRB, distributive justice pertains to the fair allocation of water resources to various stakeholders, such as countries, fishers, farmers, and local communities who are dependent on hydropower and irrigation.

Distributive justice in MOO models

Algorithms can reinforce historical human biases if they are not assessed and adapted properly (Zatarain Salazar et al., 2022). The current Sustainability Development Goals and models used by the IPCC do not encompass proper means to support the allocation of resources in a way that does not benefit the already benefitted members of society (Yalew et al., 2021; Zatarain Salazar et al., 2022). Practically, distributive justice can be implemented in EMODPS by using different utility functions to represent distributive justice or ethical principles (Dai et al., 2018) or by changing how the problem is described (Yang et al., 2023) and how objectives and preferences are aggregated (Jafino et al., 2021). The effects of disaggregation on distributive justice are built upon Arrow's paradox.

Arrow's Impossibility Theorem

Arrow's Impossibility Theorem, famously known as Arrow's paradox, presents a fundamental challenge to the aggregation of individual preferences into a constitution (Arrow, 2012). Formulated by Kenneth J. Arrow in 1950, this theorem states that "any constitution that respects transitivity, independence of irrelevant alternatives, and unanimity is a dictatorship." (Geanakoplos, 2005, p. 2). This means that a collective decision (constitution) based on ranked (transitive) votes from each individual either results in a dictatorship, or the constitution is dependent on irrelevant alternatives (the ranking changes if irrelevant alternatives are added or removed from consideration), or it does not respect unanimity (if each voter ranks alternative A above B, the constitution puts option A above B) (Kasprzyk et al., 2016). In the context of multi-objective optimization, this paradox implies that aggregating multiple objectives into a single objective can obscure the true nature of trade-offs and lead to less equitable outcomes.

Objectives disaggregation

Disaggregating objectives in simulation-optimization modelling improves distributive justice by explicitly addressing different fairness aspects, enhancing transparency, and allowing localized optimization (Kasprzyk et al., 2016). Disaggregation involves treating each objective independently rather than combining them into a single aggregated metric. This approach aligns with the fairness criteria of Arrow's Theorem by ensuring that (1) each objective has a voice, preventing any single objective from dominating the overall decision-making process and thereby adhering to the non-dictatorship criterion. (2) By maintaining separate objectives, the trade-offs between different solutions become more transparent, supporting Pareto efficiency. Additionally, this transparency is crucial for stakeholders to see how each objective is impacted by different management strategies, improving equitability in the decision-making process with no single objective unfairly influencing the overall outcome. (3) Disaggregated objectives also helps to maintain consistent preferences between solutions, even as other irrelevant alternatives are considered, thus respecting the independence of irrelevant alternatives.

1.2 KNOWLEDGE GAP

It is established knowledge that the principles of justice and fairness should be applied in simulation and optimization models focusing on climate change adaptation and the distribution of costs and benefits of (transboundary) water systems. However, due to the immense complexities and uncertainties of climate change, population demographics and multi-purpose water systems, high levels of aggregation have been needed to develop a Pareto near-optimum solution space. New modelling techniques like EMODPS allow for higher levels of objectives disaggregation, but the effects of disaggregation in EMODPS and other MOO models have not yet been researched sufficiently, especially in the water management field (Jafino et al., 2021), and have not been researched at all for the EMODPS simulation-optimization model of the ZRB. This research will focus on objective disaggregation as a means of improving the spatial intragenerational justice of the release policies of the ZRB optimization.

1.3 RESEARCH QUESTIONS

The knowledge gap will be addressed by disaggregating objectives in the existing EMODPS model of the ZRB. The research question is therefore:

How does the disaggregation of objectives influence the Pareto space in an EMODPS simulation-optimization model?

This research question will be answered by the sub questions:

1. What is the baseline configuration of objective aggregation in the current ZRB simulation-optimization model?
2. What are the impacts of the aggregations of objectives in EMODPS simulation-optimization models?
3. How do varying levels of objective disaggregation affect the complexity and feasibility of the ZRB simulation-optimization model?[1]
4. How does the disaggregation of objectives modify the derived operating policies within the ZRB model framework?

The report aims to answer these questions by first introducing the case both in practice and conceptually in chapter two. This case description will discuss the different objectives representing the WEF nexus

[1] Complexity refers to the computational cost, data complexity and the effects of many objectives on the functioning of MOEAs, monitored by convergence metrics. Feasibility refers to the curse of dimensionality, the limitations of tools and techniques to visualize large amounts of data, and other risks that come with many objective optimization, such as algorithm and hardware limitations.

in depth. In chapter three, the methodology and the model are described and elaborated on before the results of the optimizations are presented in chapter four. Chapter five provides the answers to all the research questions in the form of the conclusion an finally the implications of these conclusions, suggestions for future research and the limitations of this research are presented in the discussion section.

2 THE ZAMBEZI RIVER BASIN

The ZRB is located in southern Africa. It is the fourth largest river basin in Africa and spans across approximately 1.32 million km^2 and eight countries: Angola, Botswana, Malawi, Mozambique, Namibia, Tanzania, Zambia and Zimbabwe (Van Orshoven, Sinclair, Giuliani, et al., 2018). The origin of the Zambezi River lies in the east of Angola and the north-west of Zambia at an elevation of 1,600 meters above sea level. From here, the river flows through plains, gorges and marshlands for 2,700 km until it reaches the Zambezi Delta in Mozambique. On average, it discharges 2,600 cubic meters per second into the Indian Ocean, making it one of Africa's largest rivers by volume. High evaporation rates, ranging from 1600 mm to 2300 mm, lead to substantial water loss, which impacts the water availability for agriculture, ecosystem services and other uses.

The ZRB sustains in the needs of some 40 million people, the economic development of the eight riparian countries and an incredibly rich natural environment, covering about 5% of the African continent (*The Zambezi River basin a multi-sector investment opportunities analysis*, 2010). Despite additions of dams and irrigation infrastructure, the water supply and availability is insufficient for the water demand (Van Orshoven, Sinclair, Giuliani, et al., 2018) and a dual regional economy can be observed. Investments of more than 16 billion USD coexist with a parallel subsistence economy in which people are completely dependent on the ecosystem services provided by rivers in the basin (Lautze et al., 2017). Additionally, there is a spatial asymmetry between resource availability and population density (Van Orshoven, Sinclair, Giuliani, et al., 2018). This provides the grounds for (potential) conflicts between the riparian states and other stakeholders.

The Zambezi Watercourse Commission (ZAMCOM) plays a crucial role in the sustainable management of water resources in the ZRB (Lautze et al., 2017). Established in 2004, ZAMCOM is a collaborative organization formed by the eight riparian states of the Zambezi River. Its mission is to promote the equitable and reasonable utilization of the Zambezi River’s water resources, ensuring sustainable development. ZAMCOM facilitates cooperation among member states, focusing on water management, infrastructure development, and environmental protection. This organization is essential for addressing challenges such as the WEF nexus.

This chapter informs about the case of the ZRB by discussing developments in hydropower production, the ecosystem and irrigation in the river basin. Here, the ecosystem represents the Water aspect, hydropower represents the Energy aspect and irrigation represents the Food element of the WEF nexus. The fourth subchapter combines these aspects and discusses the river basin model within the system boundaries of this research.

2.1 Hydropower

2.1.1 Africa

There is an ongoing energy deficit on the African continent with a total demand of 605 TWh in 2012 and a total production of 441 TWh in 2000. This deficit is even more impactful when realizing that in 2014, over two-thirds of the African population did not have access to electricity (Spalding-Fecher et al., 2016; Van Orshoven, Sinclair, Giuliani, et al., 2018). Simultaneously, the energy potential in Africa is more than the potential internal energy demand. In North and West Africa, fossil fuel power production dominates the energy supply. East and Central Africa are supplied mostly by hydropower and Southern Africa's power production stems from coal power production mainly. Hydropower production on the continent has a production potential of 1200 TWh yearly, which is double the demand, but it provides only 18% of the total power production as of 2009. Less than 10% of this potential is exploited currently and over half of the potential is concentrated in Central and Eastern Africa.

The five macro-regions in Africa each have a specialized agency of their respective Regional Economic Community (REC) which are called power pools. The ZRB falls under the Southern Africa Power Pool (SAPP) which consists of eleven countries, out of which seven are in the ZRB. The SAPP has undergone much progress since its establishment in 1995, but it is still experiencing power shortages and a limited generation of transmission capacity. Approximately 16.6% of the energy demand in the SAPP was not met in 2015.

2.1.2 Zambezi River Basin

Hydropower generates nearly 80% of the total power production in the ZRB with the rest of the power coming from thermal power generation. Renewable energy production is present in the basin but it's contribution to the total energy production is negligible. The countries that produce most of the electricity are Mozambique, Zambia and Zimbabwe, all of which are responsible for approximately 25% of the total power production. There are a total of 27 hydropower plants in existence and planned in the ZRB (Van Orshoven, Sinclair, Giuliani, et al., 2018). Their production capacities vary from 88 MW to 2,075 MW (Tilmant et al., 2010; Van Orshoven, Sinclair, Giuliani, et al., 2018). Table 2-1 shows a selection of 5 dams that have been simulated in the model used for this research. Among them are the largest and most important hydropower production plants in the ZRB. The hydropower deficit is defined as demand – production, meaning a negative value indicates a production surplus. The deficit for the KGU is unknown due to it being a new hydropower station. The deficit for the Itezhitezhi hydropower station has not been found in literature.

Table 2-1: Modelled dams in the ZRB. All values have been converted to TWh/year. Kariba is a sum of Kariba North and Kariba South.. The deficit is calculated as demand – production and is calculated as an average over differing periods of time, dependent on the available data. (Power Technology, 2024; Van Orshoven, Sinclair, Giuliani, et al., 2018)

Dams	**Abbre-viation**	**Capacity [TWh/year]**	**Production [TWh/yr]**	**Deficit [TWh/yr]**	**Country**
Cahora Bassa	CB	18.18	14.73	-27	Mozambique
Kariba	KA	11.56	6.44	3.26	Zambia/Zimbabwe
Kafue Gorge Upper	KGU	8.67	5.16	0.23	Zambia
Kafue Gorge Lower	KGL	6.57	2.575	-	Zambia
Itezhitezhi	ITT	1.05	0.611	-	Zambia

Cahora Bassa

Cahora Bassa is one of the largest hydroelectric dams in Africa and the largest one in the ZRB. It is located on the Zambezi River in Mozambique. It has an installed capacity of 2,075 MW, translating to an annual generation capacity of approximately 18.18 TWh. The dam is exploited by Hidroeléctrica de Cahora Bassa (HCB) and primarily supplies electricity to Mozambique and neighbouring countries such as South Africa and Zimbabwe. About 85% of the generated energy is exported (Sebitosi & Da Graca, 2009). The power is generated through five turbines with a combined production of about 14.73 TWh annually.

Kariba

The Kariba Dam, situated on the Zambezi River between Zambia and Zimbabwe, is one of the largest man-made reservoirs in the world. It has a combined capacity of 11.56 TWh/year, with its North and South banks having capacities of 1,320 MW and 750 MW respectively. The dam’s annual production is approximately 6.44 TWh, resulting in a deficit of 3.26 TWh. The generated power is shared between Zambia and Zimbabwe, serving both countries’ energy needs. The dam is jointly operated by ZESCO (Zambia Electricity Supply Corporation) and ZPC (Zimbabwe Power Company). The dam's operation and power generation are influenced by varying hydroclimatic conditions, which necessitates adaptive management strategies to maintain efficiency and sustainability (Bertoni et al., 2019).

Kafue Gorge Upper

The Kafue Gorge Upper Hydroelectric Station is located on the Kafue River in Zambia. It has an installed capacity of 990 MW, producing approximately 5.16 TWh annually against a capacity of 8.67 TWh/year. The plant plays a crucial role in Zambia’s electricity supply, catering to both industrial and residential needs. The dam's operation and its integration with the Itezhitezhi Dam are essential for maintaining the ecological balance in the Kafue Flats (Godet & Pfister, 2007). The hydroelectric station is operated by ZESCO.

Kafue Gorge Lower

The KGU is the newest addition out of the five selected hydropower stations. The location of the hydroelectric project is 5.9 km downstream from the KGU. The dam has been developed to meet the growing electricity demands of Zambia under a PPP between the Chines SINOHYDRO and ZESCO (Sinclair et al., 2019). It has an installed capacity of 750 MW, with an annual generation capacity of 6.57 TWh.

Itezhitezhi

The Itezhi-Tezhi Dam, located on the Kafue River in Zambia, has an installed capacity of 120 MW, translating to an annual generation capacity of 1.05 TWh. Although specific production data is limited, it is estimated to produce around 0.675 TWh annually, resulting in a deficit of approximately 0.375 TWh. The dam primarily supports local electricity needs and contributes to the national grid. It is operated by Itezhi-Tezhi Power Corporation, a joint venture between ZESCO and Tata Power (Power Technology, 2024). The dam was completed in 1978 and was built to store water to ensure a steady supply for the Kafue Gorge Dam and support the local ecosystem by mimicking natural flood patterns (Godet & Pfister, 2007).

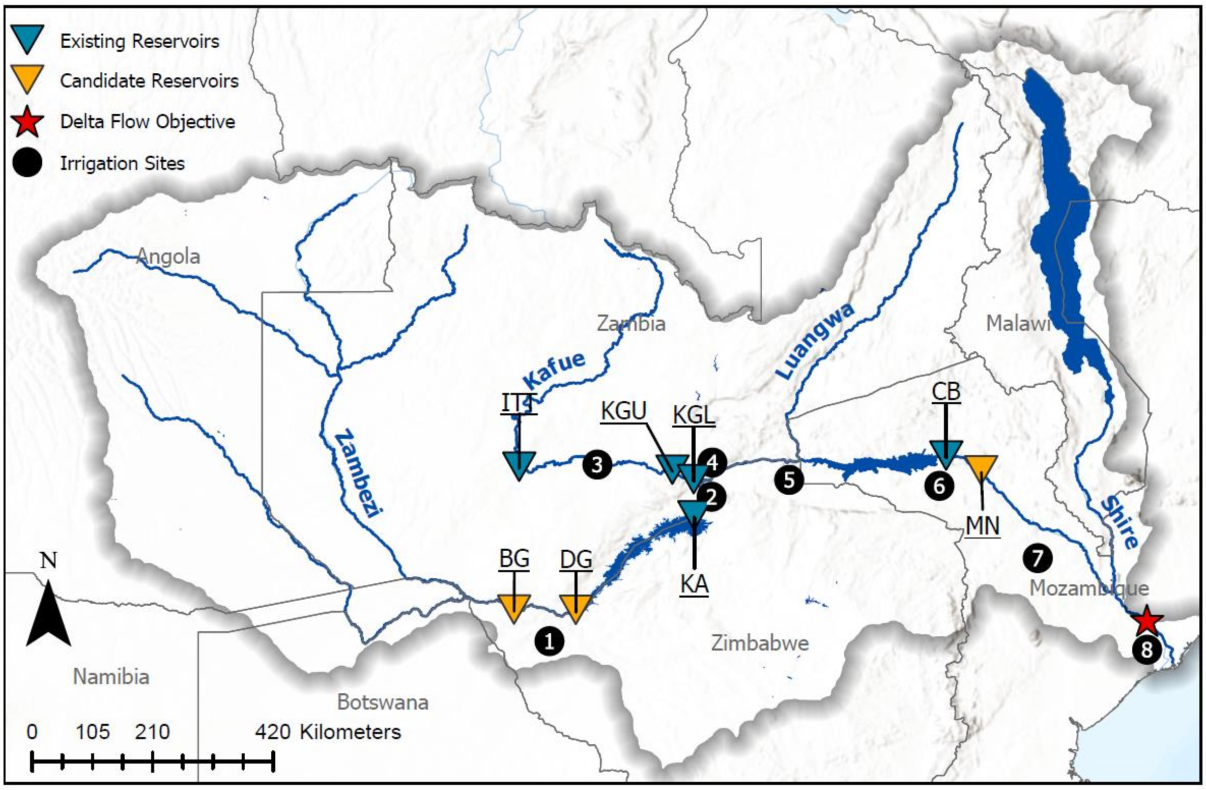

Figure 2-1: Map of ZRB with hydropower reservoirs, irrigation districts and delta. The candidate reservoirs are not considered in this research. Reprinted from (Arnold et al., 2023)

2.1.3 Challenges

The main issues with the provision of energy in the ZRB are the ongoing and planned energy deficit, the unfulfilled potential hydropower production, the infrastructure deficit and the lack of coordination between reservoir operators (Castelletti, 2019). Additionally, hydropower production in the basin is not profitable due to the unrealized potential of the hydropower plants. Coordination between the different sectors and hydropower plants can provide a solution and offers the potential to decrease the deficits on the energy market without irreversibly damaging the ecosystem or causing a food and drinking water deficit.

Other issues are the costs of the hydropower plants. In monetary terms, the power plants are not economically efficient as nearly all hydropower reservoirs have not created any profit. However, the costs of hydropower generation stretch beyond the monetary, including the displacement of communities and changes to the natural sediment and nutrient flows which are essential for maintaining the health of downstream ecosystems (Lautze et al., 2017).

2.2 ECOSYSTEM

The ZRB is home to a variety of ecosystems, including wetlands, grasslands, woodlands, and forests. The basin supports numerous plant species, many of which are endemic to the region. The ZRB features three major lakes. Lake Malawi, with a maximum depth of 695 meters, is the second deepest lake in Africa and the third deepest in the world. Lake Kariba and Lake Cahora Bassa are both man-made lakes, formed by the Kariba and Cahora Bassa dams, respectively (Van Orshoven, Sinclair, Giuliani, et al., 2018). The floodplains and dambos (seasonally flooded grasslands) are particularly rich in biodiversity. These areas provide crucial habitats for a variety of aquatic and terrestrial species. The river's wetlands are essential breeding grounds for fish and support a vibrant fishing industry that sustains local communities (Van Orshoven, Sinclair, Giuliani, et al., 2018). In addition to fish, the river and its surroundings are home to numerous amphibians, reptiles, and invertebrates. The basin is home to large populations of mammals such as elephants, buffalo, lions, and various antelope species. The riverine forests and woodlands provide habitat for these mammals, as well as for numerous bird species, making the ZRB a critical area for bird conservation. The region is also home to several threatened and endangered species, underscoring the importance of conservation efforts.

2.2.1 Ecosystem services

Ecosystem services in the ZRB are critical for the well-being of local communities and the global environment. These services include provisioning services such as freshwater, food, and raw materials; regulating services such as climate regulation, water purification, and flood control; cultural services that provide recreational, aesthetic, and spiritual benefits; and supporting services like nutrient cycling and soil formation (Lautze et al., 2017). The ZRB's ecosystem services are valued at over USD 1.3 billion annually, indicating their immense importance to both local and regional economies. Although the supply of ecosystem services currently exceeds demand, pressures on these resources are increasing due to economic development, climate change, and rapid population growth. Environmental degradation and declining water quality are posing serious threats to these services, which are vital for the livelihoods of the rural poor. Therefore, protecting these ecosystem services is crucial for poverty reduction, food security, and sustainable economic development in the Zambezi River Basin.

2.2.2 Hydroclimatic variability

The ZRB is characterized by strong hydroclimatic variability, heavily influenced by the Intertropical Convergence Zone, resulting in distinct wet and dry seasons (Castelletti, 2019). The rainy season extends from November to April, bringing much-needed water to the region, while the dry season from May to October sees significantly reduced rainfall. The basin's average annual rainfall is 950 mm, but this is unevenly distributed, with the northern and eastern regions receiving up to 1,400 mm annually, whereas the southern and western regions typically receive around 400 mm. Recent years have seen more extreme droughts and floods due to climate change, often with detrimental consequences for the local population (Lautze et al., 2017).

2.2.3 Risks to the ecosystem

The historical impact of the construction of reservoirs is limited, but it is clear that the construction and operation of dams, such as the Kariba and Cahora Bassa dams, have significantly altered the natural flow patterns of the Zambezi since the late 1970's (Calamita et al., 2018; Van Orshoven, Sinclair, Giuliani, et al., 2018). These changes have had profound effects on the river's ecosystems, particularly the wetlands in the middle and lower courses of the basin. Additionally, the regulation of river flow has affected fish migration patterns, which has had repercussions for local fisheries. All of these ecosystem services are crucial for biodiversity and local livelihoods.

Mining activities within the Zambezi River Basin have considerable environmental impacts, affecting both terrestrial and aquatic ecosystems (Ashton et al., 2001). The extraction of minerals often leads to deforestation, soil erosion, and loss of habitat for numerous species. Furthermore, mining operations can result in the contamination of water bodies with heavy metals and other pollutants, which degrade water quality and harm aquatic life. The runoff from mining sites carries toxic substances into rivers and streams, disrupting the delicate balance of these aquatic ecosystems. This contamination affects not only the biodiversity within these water bodies but also the communities that rely on them for drinking water, fishing, and agriculture. The increased sedimentation in rivers caused by mining activities can also alter the natural flow patterns and reduce the capacity of rivers to support fish populations and other aquatic organisms.

The ZRB is expected to become hotter and drier due to climate change with an increase of 0.3 to 0.6 degrees Celsius per decade, 10 to 15% less rainfall and 26 to 40% less runoff by 2050 (Lautze et al., 2017). Some research even claim the ZRB will be one of the most influenced areas by climate change (Arnold et al., 2023). These changes are expected to amplify seasonal variations, with potentially devastating consequences for agriculture. Therefore, maintaining environmental flows is essential to mitigate these impacts.

2.3 IRRIGATION

Over 60% of the inhabitants of the ZRB are active in agriculture (Lautze et al., 2017). Despite a majority of the agriculture being rainfed, irrigation for agriculture is still the main consumptive use of water in the ZRB, with irrigation being crucial for enhancing crop productivity (Van Orshoven, Sinclair, Peleg, et al., 2018). Major crops include maize, wheat, and various vegetables. Livestock farming is also prevalent, with cattle, goats, and sheep being the primary livestock. The spatial distribution of agricultural productivity is uneven, with some areas showing higher productivity due to better irrigation infrastructure and more favourable soil and climate conditions. B m^3

2.3.1 Irrigation districts

The ZRB can be divided by many different means: by country, soil type, sub-basin, land unit, administrative unit and many others. In this research, HydroSHEDS pfaffstetter[2] level 5 sub-basin levels are used in the modelling framework (see figure 2-2). It divides the river basin into 21 distinct and linked sub-basins.

There are a total of eight irrigation districts considered and modelled. An overview of these districts can be found in appendix A. For the sake of interpretation and overview, four of the eight irrigation districts are discussed in detail in this thesis. The two largest irrigation districts: Itzehitezhi and Kafue-Zambezi, and the two smallest irrigation districts: Cahora Bassa and Mphanda Nkuwa.

Itezhi-Tezhi is also referred to as irrigation district 3. It has the second highest irrigation demand out of the eight districts, after the Kafue-Zambezi district. The corresponding sub-basin is labelled as sub-basin 12261. Both the Itzehi-Tezhi and the Kafue Gorge Lower irrigation districts supply the sub-basin with irrigation water, with the latter providing approximately 10% of the irrigation inflow compared to the Itezhi-Tezhi irrigation point. The Kafue-Zambezi irrigation district is irrigation district 5 and is the largest irrigation district in terms of irrigation target release. The average annual target release is just over 100 m^3/sec. Irrigation district 6 is the Cahora Bassa irrigation district. It is the smallest irrigation district in the modelling framework with a minimal irrigation target of 0.05 m^3/sec. The second smallest

[2] https://www.hydrosheds.org

irrigation district is the Mphanda Nkuwa district, district 7. It lies in the Delta area downstream of the basin area and has a mere irrigation demand of 1.71 m³/sec.

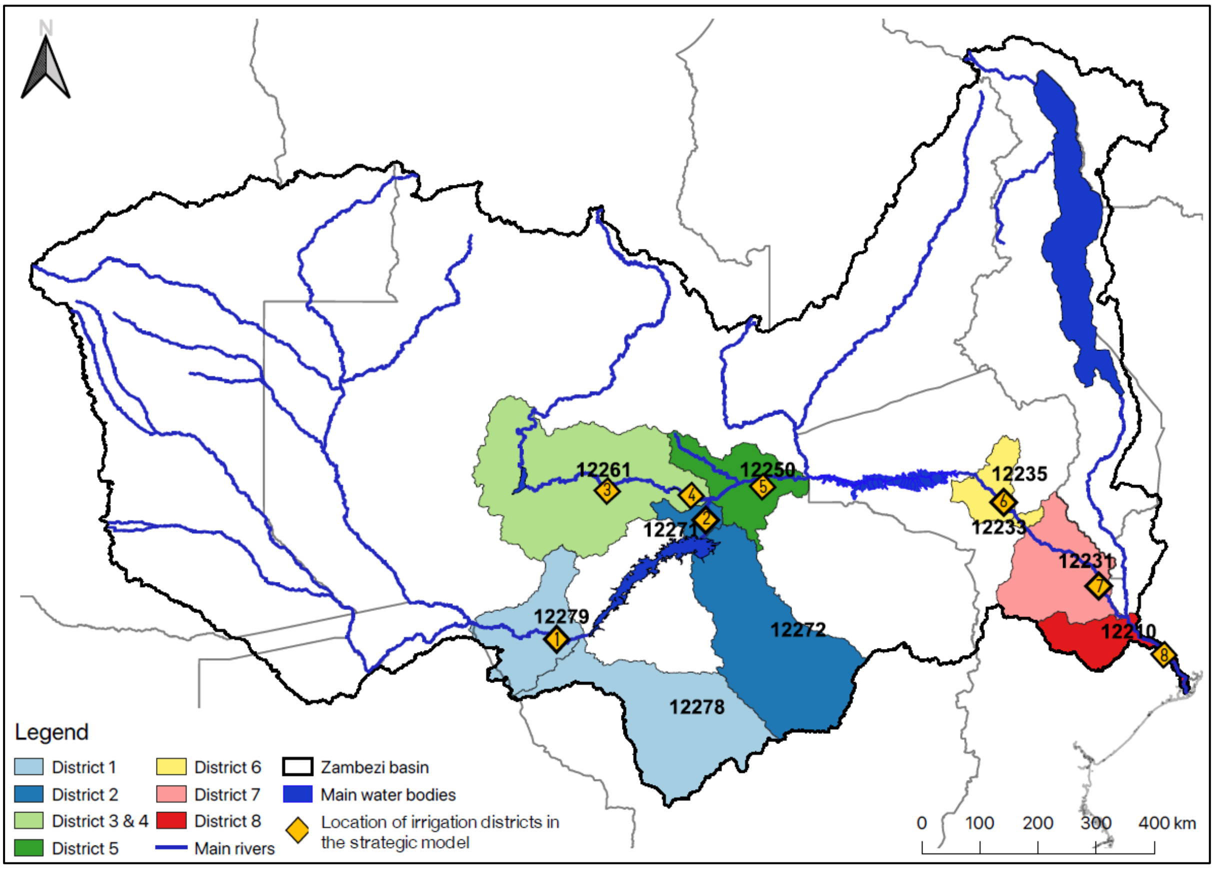

Figure 2-2: Irrigation districts with respective sub-basins. From (Van Orshoven, Sinclair, Giuliani, et al., 2018)

2.3.2 Food security

Food security is a major issue in the ZRB. There is a pressing need to increase food production and productivity due to population growth, urbanization, climate change and other elements. The predominantly small-scale nature of agriculture in the area and its dependence on precipitation, as in the most of southern Africa, causes extra challenges for the food security of the 40 million people who depend on the river basin, especially considering that the dry seasons and water scarcity are only expected to increase (Van Orshoven, Sinclair, Giuliani, et al., 2018). Approximately 80-90% of the local food production comes from small scale agriculture, which unfortunately means that the available information on these fields is very limited.

3 METHODOLOGY

This chapter presents the methodology used in this thesis. The EMODPS framework and the optimization methods for multi-reservoir systems that form its basis are the topic of subchapter 3.1. 3.2 introduces the model frameworks, the underlying mathematics and the run settings.

3.1 MULTI-OBJECTIVE OPTIMIZATIONS FOR MULTI-RESERVOIR SYSTEMS

Modelling and optimizing reservoir release policies and river basins presents unique challenges compared to other systems. Some of these complexities in modelling these systems are the data requirements and availability, dealing with multiple (competing) objectives, environmental considerations, socio-economic factors, and regulatory constraints. Additionally, sequencing decisions and the need for complex simulations to model system behaviour play key roles and are the reason for the selection of the EMODPS framework in this research.

3.1.1 Sequential decisions

Multi-reservoir systems contain multiple interconnected reservoirs and water bodies. Activities upstream (e.g., water withdrawals, dam operations) directly affect downstream water availability and quality, necessitating comprehensive basin-wide management strategies which are difficult to realise and govern (Giuliani et al., 2016). To model these sequential decisions, specific techniques and modelling capacities are required. Sequential decisions in multi-reservoir systems can be framed as a closed-loop control problem, meaning that operating policies are adapted to dynamic system conditions. These closed-loop control problems can be solved by Dynamic Programming (DP) or Stochastic Dynamic Programming (SDP). DP offers techniques to handle these complex dynamics in the system and it is used to make a series over decisions over time to find the optimal solutions. Within DP, *state variables* represent the current status of the system being managed. In the context of reservoir management, state variables include water levels, inflows, and storage capacities (Giuliani et al., 2021). *Decision variables* are the choices or actions that the decision-maker can control. For reservoir operations, these might involve the amount of water to release or retain in the reservoir. *Transition functions* capture the dynamics of the system by describing how the state variables evolve from one time step to the next, given the current state, and the decision made. The *objective function* is the function that needs to be optimized. It typically represents the goals of the reservoir management, such as minimizing flood risk, minimizing the irrigation deficit or optimizing hydropower production. SDP extends DP to incorporate stochastic system elements. *Stochastic variables* introduce uncertainty into the system. They could include random inflows from precipitation, evaporation rates, or other environmental factors that affect the reservoir. SDP is the most widely used method for optimizing water reservoir operating policies (Giuliani et al., 2016). It is a mathematical optimization technique used to solve complex decision-making problems where outcomes are partly random and partly under the control of a decision-maker. It is particularly useful in situations where decisions need to be made sequentially over time, and the system dynamics are influenced by stochastic variables.

3.1.2 Curse of dimensionality

Despite its popularity, SDP faces multiple significant challenges related to dimensionality. One of these challenges is managing temporal correlations, which involve understanding and predicting how water levels and demands change over time. This requires complex calculations and significant computational power to accurately model and forecast changes. Although dealing with sequential decisions is something that SDP addresses, it still proves a significant challenge. Specifically due to spatial correlations, which arise from the interconnected nature of water reservoirs within a network. Accurately capturing these interdependencies demands sophisticated modelling techniques and increases the computational burden. Moreover, the presence of multiple storages adds another layer of complexity. In systems with several reservoirs, each with its own storage capacity, inflow, and outflow characteristics, the number of possible states and decisions grows exponentially. This "curse of dimensionality" makes it difficult for SDP to provide optimal solutions in a reasonable timeframe. Additionally, SDP requires each dynamic influence on the system's variables to be fully modelled. This means that every factor affecting reservoir operations, such as inflows, outflows, evaporation rates, and demand patterns, must be precisely represented in the model. This level of detail further complicates the optimization process and increases the risk of errors or oversights. The use of simulations eliminates the need for detailed definitions of the factors in the system.

3.1.3 Simulation

Simulation-based optimization, specifically Direct Policy Search (DPS) offers a promising solution by eliminating the constraints associated with SDP (Giuliani et al., 2016; Giuliani et al., 2021; Herman et al., 2020) . DPS optimizes *policy functions* directly through parameter search and simulation, bypassing the need for value function computation and making it more suitable for large, complex systems and mitigating the “curse of dimensionality”. Policy functions are parameterized rules that determine the optimal actions to be taken based on the current state of the system. DPS directly uses high-fidelity simulation models that represent the real-world system, allowing for more realistic and effective optimization. DPS surpasses the "curse of modelling" as it can incorporate any simulation model and utilize exogenous data like observed inflows and precipitation directly, eliminating the need for explicit dynamic models or probability density function estimates. The goal is to find the best set of parameters for these policy functions to optimize the objective function which represents the system's performance. By focusing on policy parameters rather than state values, DPS can efficiently handle high-dimensional problems and large-scale systems (Giuliani et al., 2021). When DPS is applied to multi-objective problems, it can be effectively combined with MOO methods, providing a more robust framework for dealing with multiple objectives. The combination between MOEAs for MOO and DPS allows for flexible and efficient policy optimization, making it a valuable tool in water resource management.

3.1.4 Evolutionary Multi Objective Direct Policy Search framework

The EMODPS framework represents a sophisticated approach that integrates DPS with MOEAs and nonlinear approximating networks such as Artificial Neural Networks (ANNs) and Radial Basis Functions (RBFs) (Giuliani et al., 2016). ANNs and RBFs are used to represent policy functions. These networks provide the flexibility needed to capture complex relationships and interactions within the reservoir system. The EMODPS approach uses MOEAs to optimize the parameters of policy functions. It efficiently handles multiple objectives by generating a Pareto-optimal set of solutions, which offers trade-offs among the objectives (Zatarain Salazar et al., 2016). The use of MOEAs within the EMODPS framework allows for the discovery of high-quality representations of complex trade-offs, making it a valuable tool for integrated water resources management in the face of growing population pressures, climate change, and increased energy demands.

Limitations

One of the limitations of the EMODPS methodology is the computational demand. Although the use of policy functions reduces the computational demand compared to SDP, large and complex systems like the ZRB still require extensive computational resources (Giuliani et al., 2016). This limitation is addressed in this research by making use of High Performance Computing (HPC). When the computational demands of the supercomputer were insufficient, the optimization was divided into multiple sections, sent to the computer as individual runs and merged on a local computer.

Another "curse" that still plays a limiting role in EMODPS is scalability. As the number of objectives increases, the performance of the MOEA may decrease. The available information about the consequences of optimizing for a large number of objectives is very limited, especially for EMODPS reservoir optimization-simulation models. This research aims to provide insight into these consequences by extensive validation of the model results. The results are compared to the DAFNE research outcomes, the real-life objective values and the convergence of the outcomes is analysed and adapted to accordingly, by changing the epsilon-values and the Number of Function Evaluations (NFE).

Each of the optimization runs will provide slightly different results due to the creation of the initial random population and conditions of the MOEA (Kasprzyk et al., 2016). To account for these differences, each of the cases is run for five seeds. A detailed description of the run settings can be found in table 3-2. The results of five seeds are combined into one comprehensive set of results for each case. A non-dominated sorting process was applied to these combined results to filter out suboptimal solutions, retaining only those that are non-dominated. This means the final set of solutions represents the best trade-offs among the objectives, improving the robustness (stability across different runs) and diversity (covering a wide range of optimal solutions).

The effectiveness of EMODPS is highly dependent on the choice and tuning of the MOEAs used. Different MOEAs can yield varying levels of performance, and optimizing the parameter settings for these algorithms can be challenging and computationally intensive (Zatarain Salazar et al., 2016). For this research, the Generational Borg Algorithm (GBA) was selected.

Generational Borg Algorithm

The GBA is an advanced MOEA, building on the foundational principles of the Borg Algorithm like adaptive population sizing, auto-adaptive operator selection (mutation and crossover operators are changed over time during the running of the algorithm and smaller steps are taken in sensitive areas in the solution space), and Epsilon Progress Continuation (restart upon stagnation) (Bartholomew & Kwakkel, 2020; Hadka & Reed, 2013). These elements of the BORG algorithm are embedded into the ε-NSGAII algorithm. The GBA employs a generational update mechanism wherein the entire population is replaced in each iteration. This generational approach contrasts with the original Borg algorithm's steady-state or hybrid update methods and provides a complete refresh of the population at every generation. The use of the GBA makes sure that the epsilon progress convergence metric is implemented and adapted upon within the algorithm during the runs. The GBA is used because steady-state algorithms (like the regular BORG algorithm) may converge more slowly and because of the algorithm’s compatibility with the EMA workbench package which is used for the optimization in this research.

3.2 MODEL FRAMEWORK

The conceptual model of the ZRB consists of five hydropower reservoirs and their releases (r), eight irrigation districts, three environmentally sensitive locations with Minimum Environmental Flows (MEF), inflows (q) from the Zambezi river and the Kafue river at the most upstream locations of the basin system and six inflow points from rivers along the watercourse (figure 3-1).

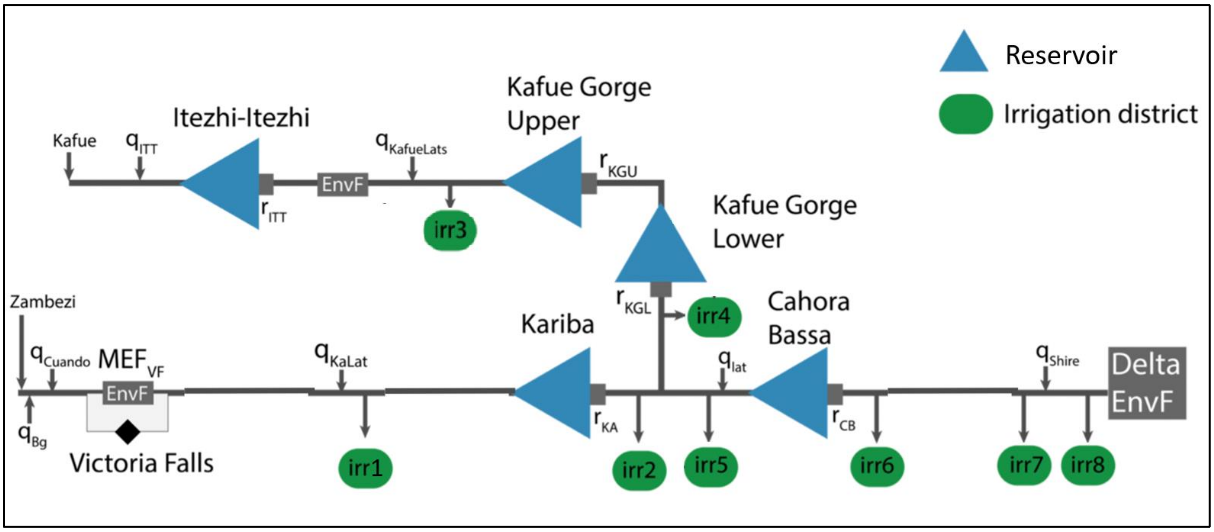

Figure 3-1: ZRB system overview, adapted from https://github.com/JazminZatarain/Multiobjective-multi-reservoir-control

As this model builds upon the work of Arnold et al. (2023), many of the functions that form the basis of the model are similar to those in their research. The input data was not altered from the model version of the DAFNE project. The data in the project was acquired though local, national and supranational institutions and agencies in light of the DAFNE project (Castelletti, 2019). Oftentimes the available data was quite limited. For example, in the western part of the basin, where there are no hydrological stations to monitor the basin. The model is built upon hydrological models, reservoir models, agricultural models, environmental models and stakeholder involvement.

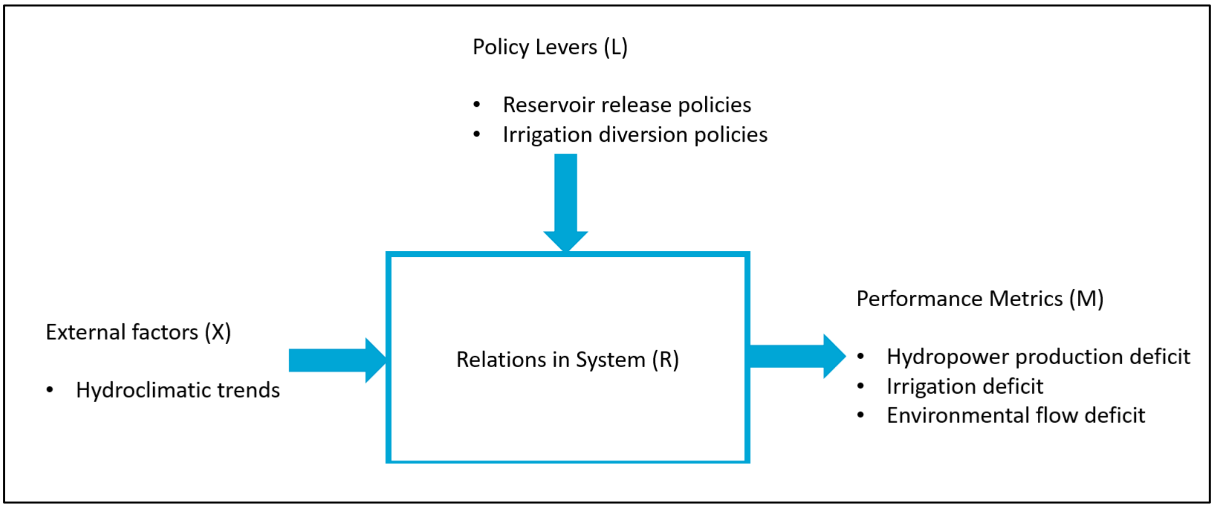

Figure 3-2: XLRM framework, adapted from Kwakkel (2017); Lempert et al. (2003)

Figure 3-2 shows the XLRM framework of the ZRB, based on the XLRM framework by Kwakkel (2017) and Lempert et al. (2003). The framework distinguishes between external factors, policy levers and performance metrics. The external factors (X) in the ZRB model are hydroclimatic trends like the inflows and precipitation in the basin. The policy levers (L) are the reservoir release policies and the irrigation diversion policies. The hydroclimatic trends and the policy levers are entered into the system

(R), where the policy functions are computed and provided as output as the performance metrics (M). These performance metrics are the objectives of the optimization.

The development of the performance metrics is an iterative process in the ZRB model, as the metrics are evaluated by the MOEA and their performance is used as input to adjust the policy levers. These adjusted policy levers are, again, put into the system and lead to new values for the performance metrics. This process iterates until the NFE or the computational limit is reached. For precise values of the NFE, see table 3-2.

3.2.1 Problem framings

The output of the simulation-optimization in the base case are the **Pareto-optimal pathways $\boldsymbol{P^*}$** with respect to the minimizing of the objectives: the hydropower deficit J^{Hyd}, the irrigation deficit J^{Irr}, and the environmental flow deficit at the Delta J^{Env} (the performance metrics in figure 3-2).

$$P^* = arg\ min_{\pi}\left(J^{Hyd}, J^{Irr}, J^{Env}\right) \tag{1}$$

Equation 1 shows the calculation of the Pareto-optimal pathways in the base case where π represents the operating policies that dictate the reservoir release and irrigation diversion decisions to achieve the desired trade-offs among the objectives.

To provide insight into the consequences of the disaggregation of objectives on the Pareto front, this research uses four different problem framings, including the base case. Table 3-1 summarizes these problem framings by detailing the case labels, the number of objectives optimized for, and the specific treatment (aggregated or disaggregated) of each deficit. This table will help clarify the differences between each framing and how they influence the optimization process.

Table 3-1: The four problem framings with corresponding levels of aggregation. The table includes columns for the problem framing label, the problem framing abbreviation, the number of objectives optimized for, and the specific treatment (aggregated or disaggregated) of the hydropower deficit in TWh/year, the normalized irrigation deficit, and the environmental flow deficit in (cm/sec)^2. Deficits are calculated as the difference between target and actual values. The hydropower production is derived from daily hydropower production (in MWh/day) and converted to an annual metric (TWh/year). The hydropower deficit is the absolute difference between this annual metric and the target production (also in TWh/year). The normalized irrigation deficit is the squared difference between target and actual irrigation volumes, divided by the target squared volume. The environmental flow deficit is calculated as the squared difference between the target flow at the Delta and the actual flow, which includes adjustments for various upstream water uses and contributions.

Problem framing label	**Abbr.**	**Number of objectives**	**Hydropower deficit [TWh/year]**	**Irrigation deficit [normalized]**	**Environmental flow deficit [(cm/sec)^2]**
Base case	BC	3	Aggregated	Aggregated	Aggregated
Hydropower case	Hyd	8	*Disaggregated*	Aggregated	Aggregated
Irrigation case	Irr	11	Aggregated	*Disaggregated*	Aggregated
Full case	Full	16	*Disaggregated*	*Disaggregated*	Aggregated

Each of the deficits is discussed in both aggregated and disaggregated forms in equations 15 through 19. The environmental flow deficit, however, is the only objective that has not been disaggregated as it is measured solely at the Zambezi Delta. This flow deficit serves as a proxy for assessing the overall environmental health and ecosystem services dependent on maintaining a more natural flow regime in the ZRB (Arnold et al., 2023). Being the most downstream point, the delta accumulates the effects of all upstream activities and alterations. Thus, monitoring the flow deficit here effectively captures the cumulative impacts of reservoir operations and other water uses throughout the basin. Other critical environmental flow points have not been included as objectives but as constraints, as the minimum environmental flow values here are hard federal requirements.

The hydropower deficit has been disaggregated in the hydropower case and the full case. For the hydropower case, the Pareto optimal pathways P^* are calculated as:

$$P^* = arg\ min_{\pi}\left(J^{Hyd}, J^{Hyd,CB}, J^{Hyd,KA}, J^{Hyd,KGU}, J^{Hyd,KGL}, J^{Hyd,ITT}, J^{Irr}, J^{Env}\right) \tag{2}$$

where $J^{Hyd,i}$ represents the hydropower deficit at reservoir i. The aggregated hydropower deficit J^{Hyd} is still considered as objective, additionally to $J^{Hyd,i}$. The aggregated hydropower objective in included in the optimization to enable a more thorough comparison between the different cases and to consider the most efficient solution accumulated over all hydropower reservoirs. The same principle is applied to the irrigation case, for which the Pareto optimal pathways are calculated as:

$$P^* = arg\ min_{\pi}\left(J^{Hyd}, J^{Irr}, J^{Irr,1}\ J^{Irr,2}, J^{Irr,3}, J^{Irr,4}, J^{Irr,5}, J^{Irr,6}, J^{Irr,7}, J^{Irr,8}, J^{Env}\right) \tag{3}$$

The irrigation objective is disaggregated for irrigation districts i in $J^{Irr,i}$ and represents the normalized irrigation deficits.

$$P^* = arg\ min_{\pi}\left(J^{Hyd}, J^{Hyd,CB}, \dots, J^{Hyd,ITT}, J^{Irr}, J^{Irr,1}, \dots, J^{Irr,8}, J^{Env}\right) \tag{4}$$

For the full disaggregation case, defined in eq. (4), all the individual hydropower and irrigation objectives, as well as the three original objectives are optimized for.

State transition functions

The problems in eq. (1) through (4) are subject to dynamic constraints imposed by the state transition function:

$$x_{t+1} = f_t(x_t, u_t, \varepsilon_{t+1}) \tag{5}$$

where ε_{t+1} represents the external drivers (like the reservoir inflow) and u_t is the sequential decision vector containing reservoir releases and irrigation diversion policies. The time steps in the model are months, with a total runtime of 240 months (20 years). Most of the sequential relations have a negligible travel time.

The mass-balance formulations define how the reservoir storages and how cascading flows change dynamically from reservoir to reservoir. The relations between the reservoir storages, visualized in figure 3-1, are as follows:

$$s_{t+1}^{KA} = s_t^{KA} + (q_{t+1}^{VF} + q_{t+1}^{KA} - \omega_{t+1}^{1}) - e_t^{KA} S_t^{KA} - r_{t+1}^{KA} \tag{6}$$

$$s_{t+1}^{ITT} = s_t^{ITT} + q_{t+1}^{ITT} - e_t^{ITT} S_t^{ITT} - r_{t+1}^{ITT} \tag{7}$$

$$s_{t+1}^{KGU} = s_t^{KGU} + \left(q_{t+1}^{KGU} + r_{t+1}^{ITT} - \omega_{t+1}^{3}\right) - e_t^{KGU} S_t^{KGU} - r_{t+1}^{KGU} \tag{8}$$

$$s_{t+1}^{KGL} = s_t^{KGL} + r_t^{KGU} - e_t^{KGL} S_t^{KGL} - r_{t+1}^{KGL} \tag{9}$$

$$s_{t+1}^{CB} = s_t^{CB} + \left(q_{t+1}^{CB} + r_{t+1}^{KGL} + r_{t+1}^{KA} - \omega_{t+1}^{2} - \omega_{t+1}^{4} - \omega_{t+1}^{5}\right) - e_t^{CB} S_t^{CB} - r_{t+1}^{CB} \tag{10}$$

where s_t^i is the initial storage of reservoir *i* per month, $q_{t+1}^i$is the reservoir inflow, $\omega_{t+1}^j$is the irrigation diversion volume from the *j*-th irrigation district and r_{t+1}^i is the water release volume of reservoir *i* (eq. (11)) and e_t^i is the average monthly evaporation rate. S_t^i is the reservoir surface which is defined by a non-linear relation based on s_t^i. $e_t^i S_t^i$ is the evaporated water in time interval [t, t+1) (Arnold et al., 2023). The evaporation rate at the KGU has been calibrated differently due to significant losses due to evaporation at the Kafue Flats (Gandolfi et al., 1997). Water release volume r_{t+1} at reservoir *i* is:

$$r_{t+1}^i = f\left(s_t^i, u_t^i, q_{t+1}^i, e_t^i\right) \tag{11}$$

where the stochastic, non-linear relation between the release decision ($u_t^i = \rho_\theta^*$) following from the operating policy and the actual release is captured by f(.) (Piccardi & Soncini-Sessa, 1991). The actual release is usually equal to the release decision by the end of the monthly time interval, unless the release is prohibited by capacity restraints.

Operating policies

The two policies in the ZRB model; reservoir release policies ρ_θ and the irrigation diversion policies θ_ω compose the operating policy π which determines the coordinated operations of the reservoir network.

Candidate control policies for the reservoir releases are initializes as highly parameterized nonlinear approximating networks, by the use of non-convex Gaussian RBFs. The *k*-th release decision in the R-dimensional decision vector u_t is defined as:

$$u_t^k = \delta_k + \sum_{i=1}^{N} \omega_{i,k}\varphi_i(I_t) \tag{12}$$

where δ_k is the constant linear parameter, N is the number of RBFs φ_i, I_t is the policy input, and $\omega_{i,k}$ is the non-negative weight of the *i*-th RBF. The following definition applies to a single RBF:

$$\varphi_i(I_t) = \exp\left[-\sum_{j=1}^{M} \frac{\left[(I_t)_j - c_{j,i}\right]^2}{b_{j,i}^2}\right] \tag{13}$$

where *M* equals the number of policy input variables *I*, *b* and *c* are the M-dimensional radius and centre vectors of the *i*-th RBF with $b_{j,i} \in (0,1]$ and $c_{j,i} \in [-1,1]$. The multi-dimensional reservoir operating policy is defined as $\theta = \left[\delta_k, b_{i,j}, c_{i,j}, \omega_i\right]$ with *i* = 1,…,N, *k* = 1,…,R, *j* = 1,…,M. Policy inputs vary from reservoir storage to time and inflows. Full reservoir network coordination is assumed.

The irrigation diversion policies θ_ω define water diverted for irrigation per district (ω^{id}) with a non-linear hedging rule:

$$\omega_{t+1}^{id} = \begin{cases} \min\left(q_{t+1}, v_t^{id} \cdot \left[\frac{q_{t+1}}{h^{id}}\right]^{m^{id}}\right) & if\ q_{t+1} \leq h^{id} \\ min\left(q_{t+1}, v_t^{id}\right) & else \end{cases} \tag{14}$$

with the volume of available water at the district diversion point being q_{t+1}, the monthly water demand as v_t^{id}, and m^{id} and h^{id} being regulatory parameters for the diversion channel.

Objective functions

The hydropower deficit (minimize) represents the energy sector with the annual average hydropower energy production deficit in TWh/year either as a sum over all hydropower reservoirs J^{Hyd} in eq. (15) or disaggregated for the five hydropower reservoirs *i* in the system $J^{Hyd,i}$ eq. (16).

$$J^{Hyd} = \frac{1}{N}\sum_{t=0}^{H} |T_t^{HP,i} - HP_{t+1}^{i}|_{i=1,\dots,I} \tag{15}$$

$$J^{Hyd,i} = \frac{1}{N}\sum_{t=0}^{H} |T_t^{HP} - HP_{t+1}| \tag{16}$$

where N is the number of years in planning horizon H, $T_t^{HP,i}$ is the hydropower target production at the i-th hydropower plant and HP_{t+1}^{i} is the actual production at said hydropower plant. The hydropower production is defined using the standard power generation formula: $\eta^i g\gamma\bar{h}_t^i q_{t+1}^{turb,i}$ where η is the turbine efficiency, g is the gravitational acceleration (9.81 m/s^2), the water density is γ (1,000 kg/m^3),

$\bar{h}_t^i$ is the hydraulic head and $q_{t+1}^{turb,i}$ is the turbinated flow in m³/sec. The hydropower production targets T_t^{HP} have been developed by Arnold et al. (2023) using TEMBA, which is a South African power grid model from the open source OSeMOSYS (Taliotis et al., 2016). The hydropower deficit is defined as the absolute difference between the target and the actual production.

The irrigation deficit (minimize) represents food security in the ZRB by calculating the normalized irrigation deficit either as a sum over all the districts in eq. (17) or per district in eq. (18):

$$J^{Irr} = \frac{1}{H}\sum_{t=0}^{H}\left(\frac{max\left(T_t^{irr,id} - \omega_{t+1}^{irr,id}, 0\right)}{T^{irr,id}}\right)^2_{id=1,\dots,ID} \tag{17}$$

$$J^{Irr,id} = \frac{1}{H}\sum_{t=0}^{H}\left(\frac{max\left(T_t^{irr} - \omega_{t+1}^{irr}, 0\right)}{T^{irr}}\right)^2 \tag{18}$$

where H Is the planning horizon, $T_t^{irr,id}$ is the irrigation diversion demand and $\omega_{t+1}^{irr,id}$ is the actual diversion volume for district *id*. According to Arnold et al. (2023) the normalization of the irrigation deficits prevents the optimization from favouring one district over the other by means of their target diversion demand. The irrigation deficit is normalized by dividing the actual irrigation diversion volume by the irrigation diversion target and then squaring the result. The deficit has a minimum of zero.

The environmental flow deficit (minimize) is the flow deficit at the Delta downstream of the river basin. Specifically, the flow deficit measure captures the extent to which the actual flows (governed by upstream reservoir releases and irrigation diversions) fall short of the target environmental flows. The flow deficit proxies the environmental health and ecosystem services dependent on the natural flow regime (Arnold et al., 2023). The deficit is defined as:

$$J^{Env} = \frac{1}{H}\sum_{t=0}^{H}(\max\left(T_t^{env} - r_{t+1}^{env}, 0\right))^2 \tag{19}$$

where H is the planning horizon, T_t^{env} is the target environmental flow and r_{t+1}^{env} is the actual flow as a result of the upstream irrigation and release decisions. The sum of squared flow deficits is averaged over the planning horizon H. T_t^{env} is set to 0 for all months except February and March, when it is equal to 7,000 m³/s (Arnold et al., 2023; Tilmant et al., 2010).

Constraints

The environmental flow objective does not include the environmental flow deficits upstream, but merely at the Delta (Arnold et al., 2023). These sensitive upstream environmental requirements are formulated as constraints within the model, because the minimum environmental flows at these points in the system are federal requirements. These constraints are the environmental flows at the Victoria

Falls and at the Itezhi-Tezhi reservoir. At the Victoria Falls a minimum of 250 m^3/s is left in the river every month and cannot be turbinated for hydropower production. The Itezhi-Tezhi reservoir has to release at least 40 m^3/s per month in environmental flow, except in March when it has to release a minimum of 315 m^3/s to maintain natural flooding patterns. Other physical constraints are included in the model as well, such as the minimum and maximum inflows and releases in turbines and storage capacity constraints.

3.2.2 Experimental setup

The run settings for each of the cases are shown in table 3-2. Here, the NFE, the pseudo-random seeds, the abbreviations of the included objectives and the ε-values for the optimization and the merging of the results is shown for each of the four cases.

The base case and the hydropower case both are optimized by use of 200,000 function evaluations, the irrigation case and full case are both optimized with 1,000,000 function evaluations. The NFE was determined by trial and error through observing the convergence metrics. The hypervolume metric is calculated ex post, using the runtime data which is stored per 100 NFEs. However, when the computational limits were reached, The irrigation and full case both did not display convergence after 500,000 NFE and therefore the decision was made to utilize the maximum computational resources by running these cases for 1,000,000 NFE per seed.

The results from five separate seeds were merged using epsilon non-dominance to ensure a representative and manageable set of solutions. All epsilon values are based on trial and error so that the merged Pareto set would contain approximately 100 solutions. The individual runs per seed contained approximately 100 results by usage of the optimization ε-values. In order to ensure that the merged results also contained around 100 results, different ε-values were used for merging the results.

The settings for the RBFs can be seen in table 8-2. The inputs used for the release policies' 11 non-convex RBFs are the storage levels of the ITT, KGU, KA, CB and KGL reservoirs, the month of the year and the sum total of the reservoir inflows.

Table 3-2: Run settings. A summary of the run settings for each of the four cases is presented with the NFE, pseudo-random seeds used for initialization, the abbreviation of the objectives for which is optimized, the epsilon values used for the optimization and the epsilon values used for the merging of the results. The epsilon values were selected based on trial-and-error with the goal of maintaining a well-balanced selection of results for the optimization and to maintain a manageable amount of solutions for the merging of the results.

	Base case	**Irrigation case**	**Hydropower case**	**Full case**
NFE	200,000	1,000,000	200,000	1,000,000
Seeds	[17, 42, 63, 188, 1234]	[17, 42, 63, 188, 1234]	[17, 42, 63, 188, 1234]	[17, 42, 63, 188, 1234]
Objectives	Hyd, Env, Irr	Hyd, Env, Irr, Irr2,…,Irr8	Hyd, Env, Irr, HydITT,…, HydKGL	Hyd, Env, Irr, Irr2,…,Irr8, HydITT,…,HydKGL
ε-values optimization	[0.20, 0.50, 0.30]	[0.40, 0.60, 0.50, 0.70, 0.70, 0.70, 0.70, 0.70, 0.70, 0.70, 0.70]	[0.90, 1.00, 0.90, 1.20, 1.20, 1.20, 1.20, 1.20]	[0.90, 1.00, 0.90, 1.20, 1.20, 1.20, 1.20, 1.20, 1.20, 1.20, 1.20, 1.00, 1.00, 1.00, 1.00, 1.00]
ε-values merging	[0.40, 0.40, 0.40]	[0.68, 0.68, 0.68, 0.68, 0.68, 0.68, 0.68, 0.68, 0.68, 0.68, 0.68]	[1.30, 1.30, 1.30, 1.30, 1.30, 1.30, 1.30, 1.30]	[1.50, 1.50, 1.50, 1.50, 1.50, 1.50, 1.50, 1.50, 1.50, 1.50, 1.50, 1.50, 1.50, 1.50, 1.50, 1.50]

Table 3-3: Radial Basis Functions settings table. The seven inputs for the RBF are the storage levels of the five reservoirs in m^3 (see mass-balance equations 6 through 10), the month of the year and the sum total of the reservoir inflows in m^3/sec. The five outputs are the reservoir release decisions (in m^3/sec). The number of free parameters is calculated as K+N(M*2+K) where K is the number of outputs, N is the number of RBFs and M is the number of inputs.*

Parameter	**Value**
Name	Release
Type	Non-convex Gaussian Radial Basis Function
Number of Inputs (M)	7
Number of Outputs (K)	5
Number of RBFs (N)	11
Number of free parameters	304
Inputs	$[s_t^{ITT},\ s_t^{KGU},\ s_t^{KA},\ s_t^{CB},\ s_t^{KGL},\ moy_t,\ q_t^{tot}]$
Input maximum	[5883000000.00, 1178000000.00, 180798000000.00, 51704000000.00, 62840000.00, 12.00, 11213.58]
Input minimum	[699000000.00, 5000000.00, 116054000000.00, 32000000.00, 10950000.00, 1.00, 0.00]
Outputs	$[u_t^{ITT}, u_t^{KGU}, u_t^{KA}, u_t^{CB}, u_t^{KGL}]$
Output maximum	[7338.28, 2894.46, 11539.94, 15859.70, 4445.97]
Output minimum	[0.00, 0.00, 0.00, 0.00, 0.00]

4 Results

This chapter discusses the results of the EMODPS simulation-optimization by discussing the trade-offs between the aggregated hydropower, the aggregated irrigation and the environmental flow objective, discussing the influence of the cases on the different deficits both in total and locally and finally, by discussing the convergence metrics and the statistical analysis of the results. Each of the sections discusses the four cases simultaneously to accommodate an immediate comparison. For an overview of all results per district and reservoir, see appendix D.

4.1 Trade-offs

The trade-offs between the three main objectives are observed for all the four cases: the base case with three objectives, the irrigation case with 11 objectives, the hydropower case with eight objectives and the full case with 16 objectives. For a full overview of all the parallel axis plots used to visualize the trade-offs, refer to appendix D.2. The parallel axis plots highlight the best solutions for each of the objectives. By creating an axis and showing the value this best solution takes on for each of the other objectives, a comparison of the trade-offs between these objectives is possible.

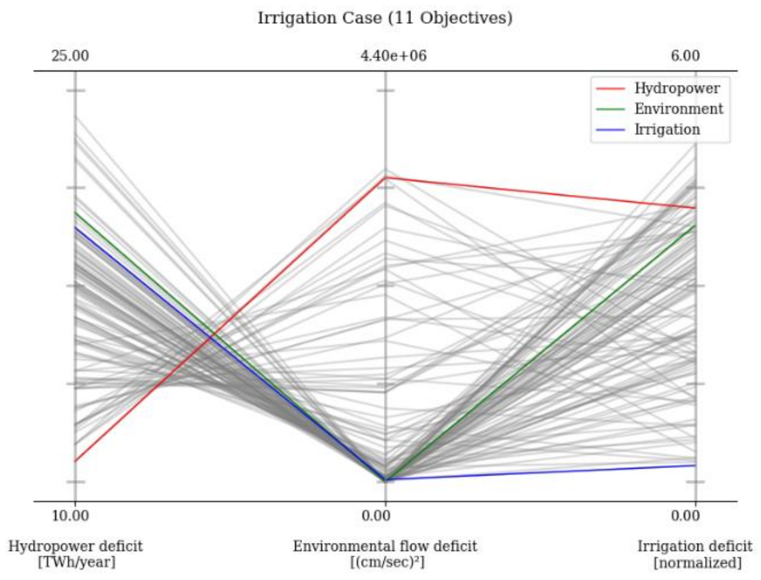

Figure 4-1: Parallel axis plot showing the trade-offs between the three base objectives (hydropower deficit in TWh/year, the environmental flow deficit in (cm/sec)^2 and the normalized irrigation deficit) for the irrigation case (optimized for 11 objectives). The parallel plots for the other cases are shown in appendix D.2. This figure is included here to support the storyline and provide an example of the differences in trade-offs between the best solutions for the different deficits. Each of the coloured lines represents a best solution, meaning that the value of this line reaches (closest to) zero for a particular objective, as the direction of preference is downward.

The best solution for the hydropower objective consistently shows conflict with the irrigation and environmental flow objectives, meaning that the lowest hydropower deficit causes a high irrigation deficit and a high environmental flow deficit in all of the cases. This can be seen in the red line in figure 4-1. The solution with the most beneficial policies for the environmental flow deficit presents a significant trade-off with the irrigation and hydropower deficits as well. However, other 'good' solutions for the environmental flow deficit show a much lower trade-off with the irrigation deficit in the disaggregated cases. This is illustrated by the blue line, which represents the best solution for the irrigation deficit. It can be seen that this best irrigation solution causes a very low environmental flow deficit. This trend is visible for all the disaggregated cases, but not for the base case. This implicates that beneficial solutions for the irrigation deficit and the environmental flow deficit can coincide with each other more easily in the Pareto set of solutions of the disaggregated cases.

4.2 DEFICITS

This subsection visualizes and summarizes the impacts that the different cases have on the hydropower, irrigation and environmental flow deficits. First, the mean deficits per year are compared and hereafter, the relative deficits per case are shown to provide the basis for a proper comparison between the cases.

4.2.1 Mean deficits

The Pareto set of solutions of each of the cases has been visualized through a boxplot. Each boxplot contains the objective values for one of the three original objectives: the hydropower deficit (figure 4-2), the irrigation deficit (figure 4-3) and the environmental flow deficit (figure 4-4).

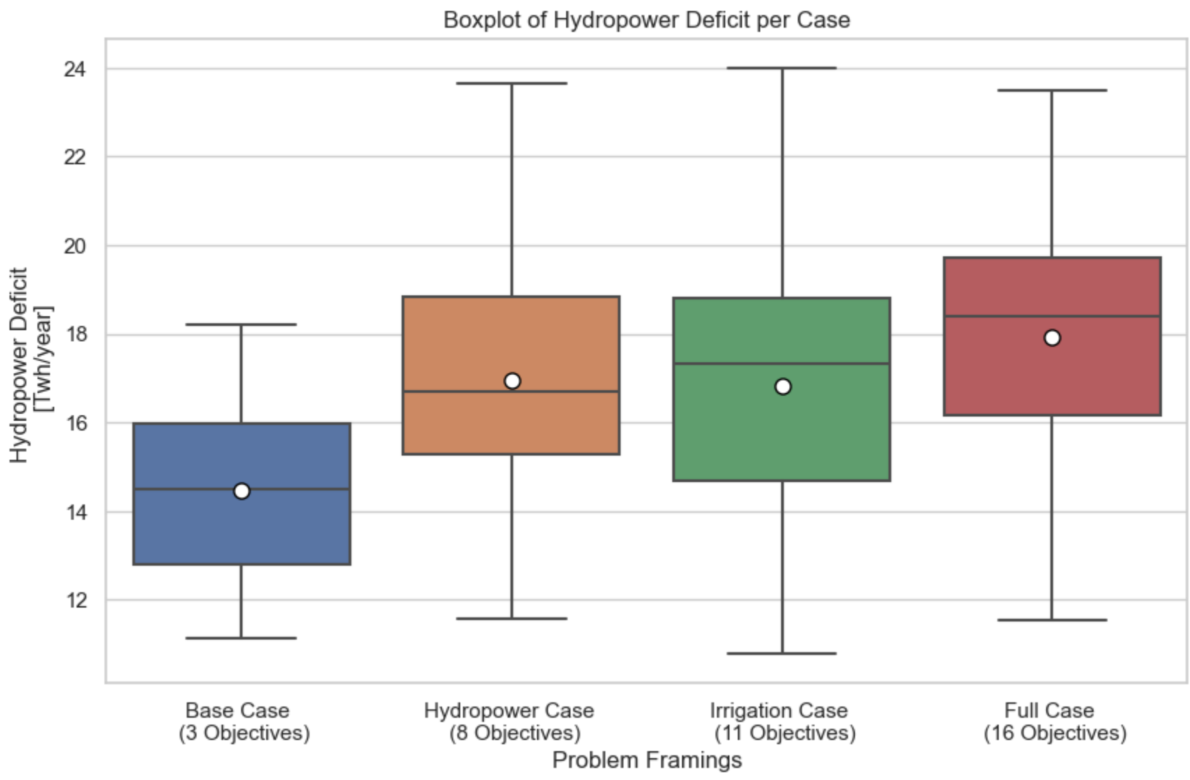

Figure 4-2: Boxplot of hydropower deficit objective (in TWh/year) solution space per case. The hydropower deficit is the absolute difference between the daily production deficit (MWh/day), converted to TWh/year and the target production (also in TWh/year). The white dot indicates the mean.

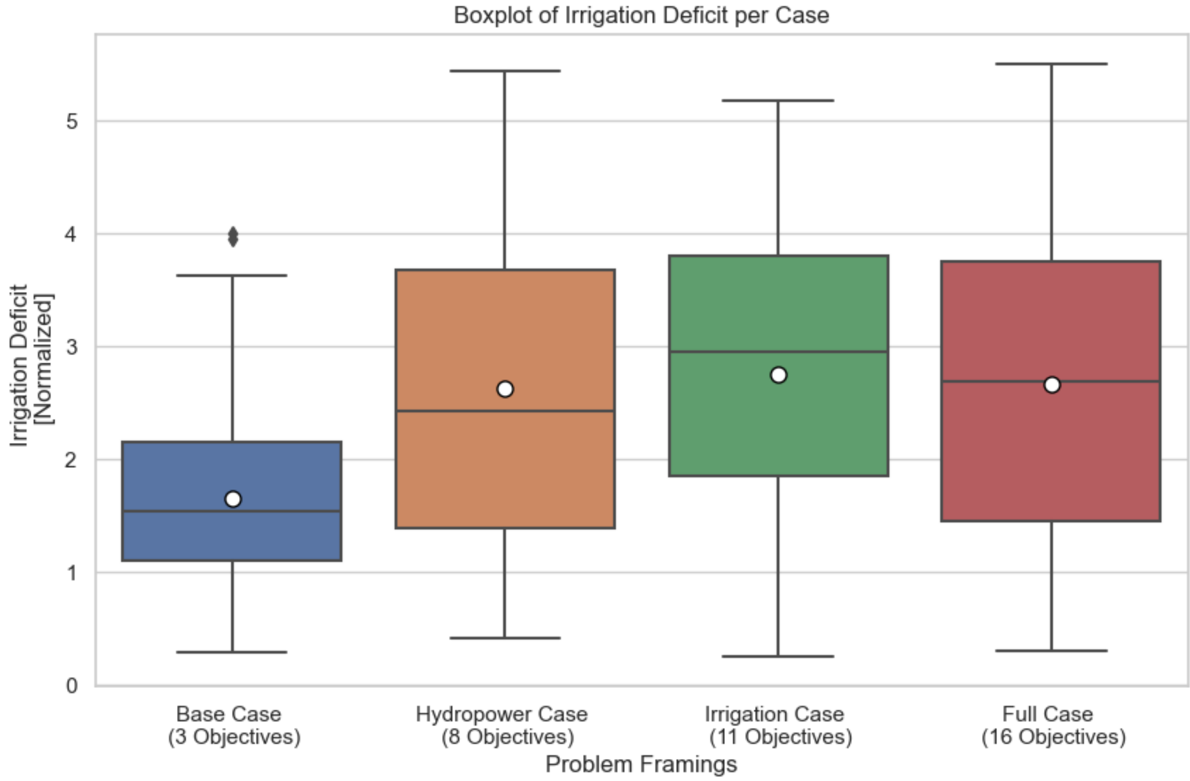

Figure 4-3: Boxplot of irrigation deficit objective solution space per case. The normalized irrigation deficit is the squared difference between target and actual irrigation volumes, divided by the squared target volume. The white dot indicates the mean.

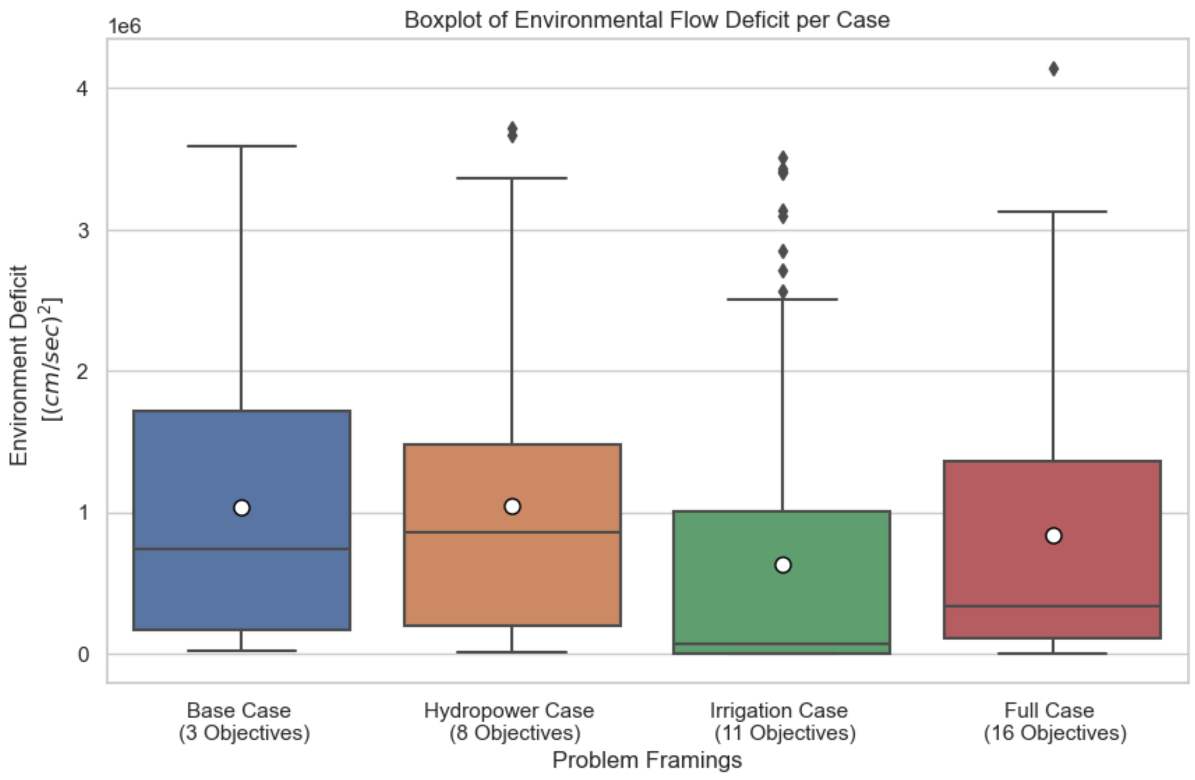

Figure 4-4: Boxplot of environmental flow deficit objective (in $(cm/sec)^2$) solution space per case. The environmental flow deficit is calculated as the squared difference between the target flow and the actual flow. The white dot indicates the mean.

Hydropower deficit

The solution space of the base case generally contains policies which cause lower hydropower deficits than the disaggregated cases, as the maximum deficit within this Pareto set of solutions is considerably lower than that of the other cases (figure 4-2). The Inter Quartile Range (IQR) of the fully disaggregated case lies slightly higher than that of the other disaggregated cases, suggesting that the full case performs the worst out of the four levels of aggregation when it comes to the hydropower deficit in the Pareto set.

Irrigation deficit

The boxplot for the irrigation deficit shows a similar pattern to that of the hydropower deficit (figure 4-3). The base case, optimized for three aggregated objectives, has a solution space that is more beneficial for the total irrigation deficit. The IQR of the base case is also noticeably smaller than that of the other cases, indicating a more concentrated solution space, with lower deficits.

Environmental flow deficit

The distributions of the environmental flow deficit per case (figure 4-4), shows a different pattern than the other deficits in figures 4-2 and 4-3. Here, the base case does not perform visibly better than the other cases. This is peculiar, because the environmental flow deficit is the only objective which has not been disaggregated. This indicates that the disaggregated problem framings have taken the environmental flow deficit at least as much into account as the base case with three objectives has done. The environmental flow objective is the only objective that has not been disaggregated and it is the only objective for which the median of the base case is not lower than the other cases. The disaggregated irrigation case and the fully disaggregated case both have a lower median deficit than the base case for this objective.

4.2.2 Relative deficits

Tables 4-1 and 4-2 show the relative irrigation and hydropower deficits for each irrigation district and hydropower reservoir in the ZRB. The relative deficits are defined as the share of the deficits of the target demand or production [deficit/demand]. The data used for the normalized deficits calculation are the mean deficits throughout the runtime for the optimized 'best' solutions of the three base objectives: the best solutions for the hydropower deficit, for the irrigation deficit and for the environmental flow deficit.

Table 4-1: Relative irrigation deficits per case per irrigation district. The irrigation districts are ranked from largest to smallest based on their target demand (the ranking would be the same if it were based on actual irrigation diversion volumes). The average deficits are presented (being the share of the target demand that is actually diverted) per case. The values of the relative deficits are ranked by severity, with a darker red representing a larger deficit.

Ranking: largest to smallest	**ID**	**Irrigation district**	**Target demand** [m³/sec]	**Average deficits** [% of target demand]			
				BC (3 obj)	**Hyd** (8 obj)	**Irr** (11 obj)	**Full** (16 obj)
1	5	Kafue-Zambezi	100.08	0.42	0.47	0.42	0.49
2	3	Itezhitezhi	36.42	0.46	0.54	0.52	0.52
3	8	Shire-Zambezi	31.31	0.00	0.32	0.40	0.29
4	2	Kariba	19.11	0.03	0.30	0.48	0.51
5	1	Batoka Gorge	7.24	0.49	0.03	0.01	0.14
6	4	Kafue Gorge Lower	3.59	0.07	0.13	0.42	0.30
7	7	Mphanda Nkuwa	1.74	0.24	0.56	0.30	0.22
8	6	Cahora Bassa	0.05	0.25	0.67	0.17	0.22

The relative irrigation deficits in table 4-1 show that there is not a clear pattern or visible relation between the aggregation levels and the irrigation deficits per district. Overall, the base case offers the best solutions for the irrigation districts with a sum total of the relative deficits being 1.96 compared to 2.72, 3.02 and 2.96 for the irrigation case, hydropower case and full case respectively. The Batoka Gorge district is an exception to the superior performance of the base case as the disaggregated cases provide more advantageous solutions for this middle-sized irrigation district than the aggregated base case does. The Kariba irrigation district shows an opposite effect, as the irrigation deficit holds a minimal share of the irrigation diversion demand in in the highly aggregated base case, as opposed to the irrigation case and full case in particular. Notable is that the two largest irrigation districts have an irrigation deficit share of more than 40 per cent in all of the cases. The large districts are effected minimally by disaggregating the objectives.

Table 4-2: Relative hydropower deficits per case. The hydropower reservoirs are ranked from largest to smallest based on their target production (the ranking would be the same if it were based on actual hydropower production). The average hydropower deficits are presented (being the share of the target production that is actually produced) per case. The values of the relative deficits are ranked by severity, with a darker red representing a larger deficit.

Ranking: largest to smallest	**Reservoir**	**Abbr.**	**Production target [TWh/year]**	**Average hydropower deficits [% of target production]**			
				BC (3 obj)	**Hyd** (8 obj)	**Irr** (11 obj)	**Full** (16 obj)
1	Cahora Bassa	CB	14.49	0.46	0.53	0.58	0.58
2	Kariba	KA	9.11	0.64	0.77	0.66	0.71
3	Kafue Gorge Upper	KGU	4.77	0.13	0.27	0.20	0.26
4	Kafue Gorge Lower	KGL	3.40	0.23	0.44	0.37	0.44
5	Itezhitezhi	ITT	0.57	0.42	0.56	0.54	0.59

The relative hydropower production deficits do not show a correlation between the levels of aggregation and the deficits. Additionally, there is no apparent advantage or disadvantage of being either a smaller or larger reservoir when the objectives are disaggregated. Similarly to the relative irrigation deficits, the hydropower deficit shares are smaller for the base case than for the disaggregated cases. All of the relative deficits are smaller in the aggregated base case than they are when objectives are disaggregated. Independently of whether the hydropower deficit of that specific hydropower reservoir is optimized for as an objective.

4.3 EVALUATION OF OPTIMIZATION PERFORMANCE

Due to the large amount of objectives that have been optimized for, it is important to monitor the performance of the optimization. This monitoring is done by conducting a convergence analysis. A statistical analysis is conducted additionally to conclude whether there are significant differences between the levels of aggregation.

4.3.1 Convergence analysis

Convergence analysis is of particular interest in this research because it provides insights into how effectively the algorithm handles many objectives. The cases with more than 10 objectives, being the irrigation case with 11 objectives (figure 4-7) and the full case with 16 objectives (figure 4-8), exhibit unusual behaviour in the hypervolume metric, characterized by dips. When initially run with 200,000 function evaluations, these cases showed no observable convergence, whereas the base case (figure 4-5) and the hydropower case (figure 4-6) do demonstrate clear patterns of convergence. After trial and error, the irrigation and full cases were run with 1,000,000 function evaluations, which was the computational limit. Each of the 5 seeds with 1,000,000 NFE has a runtime of more than 5 days on the

DelftBlue supercomputer[3]. The computational cost for the highly disaggregated irrigation case and the full case is significantly higher compared to the more aggregated ones (the base case with three objectives and the hydropower case with eight objectives). The total computational time to optimize the irrigation and full case is 120 hours * 5 seeds = 600 hours. The computational time of the base and hydropower case is 120 hours for the total 5 seeds.

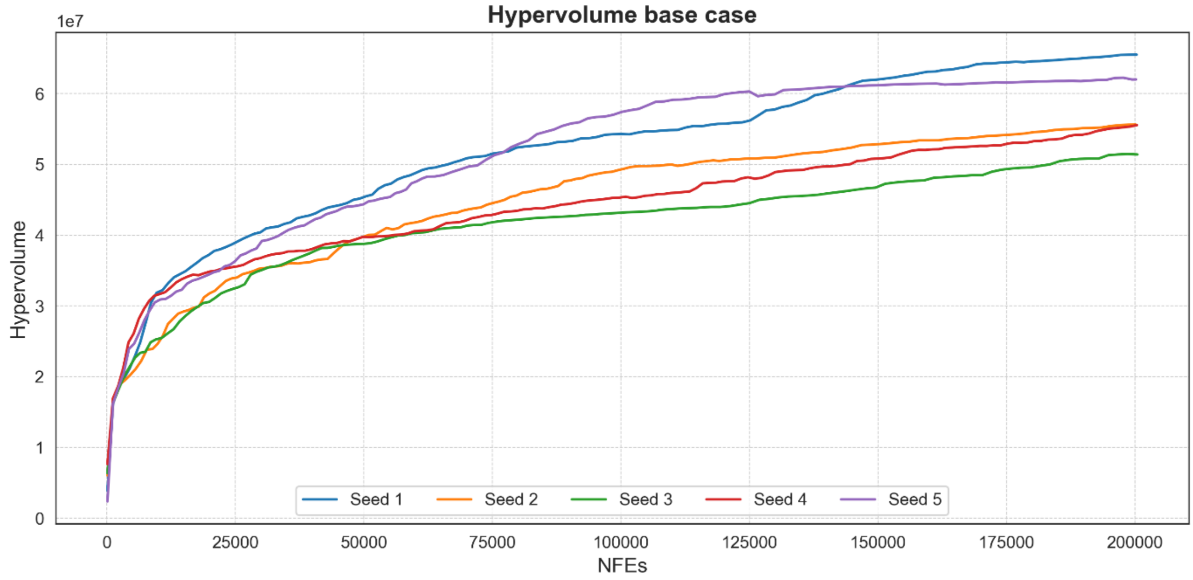

Figure 4-5: Hypervolume metric for base case (3 objectives). The base case was run for 200,000 NFEs over five seeds and shows convergence.

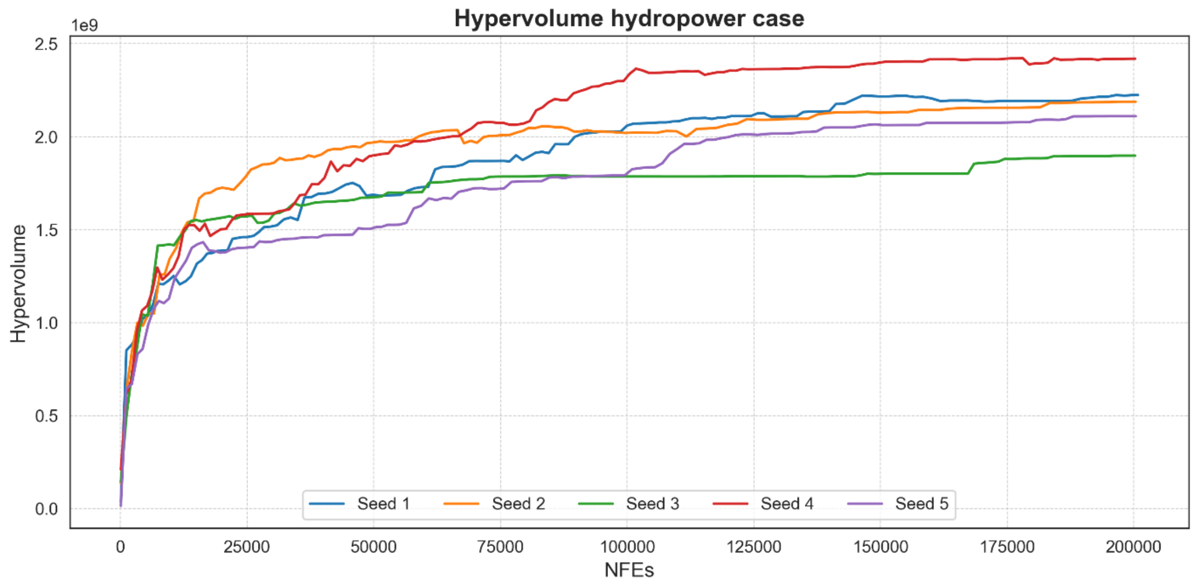

Figure 4-6: Hypervolume metric for hydropower case (8 objectives). The hydropower case was run for 200,000 NFEs over five seeds and shows convergence, with small dips.

[3] https://www.tudelft.nl/dhpc/system

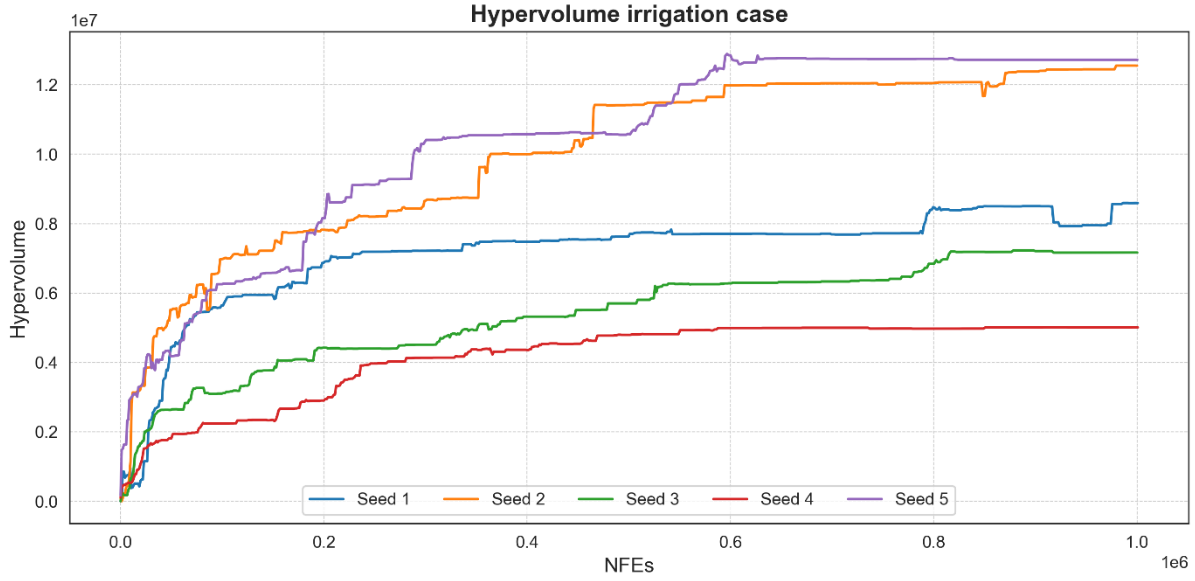

Figure 4-7: Hypervolume metric for irrigation case (11 objectives). The irrigation case was run for 1,000,000 NFEs over five seeds. The hypervolume shows unwanted behaviour, specifically visible around the 900,000 NFE mark for seed 1.

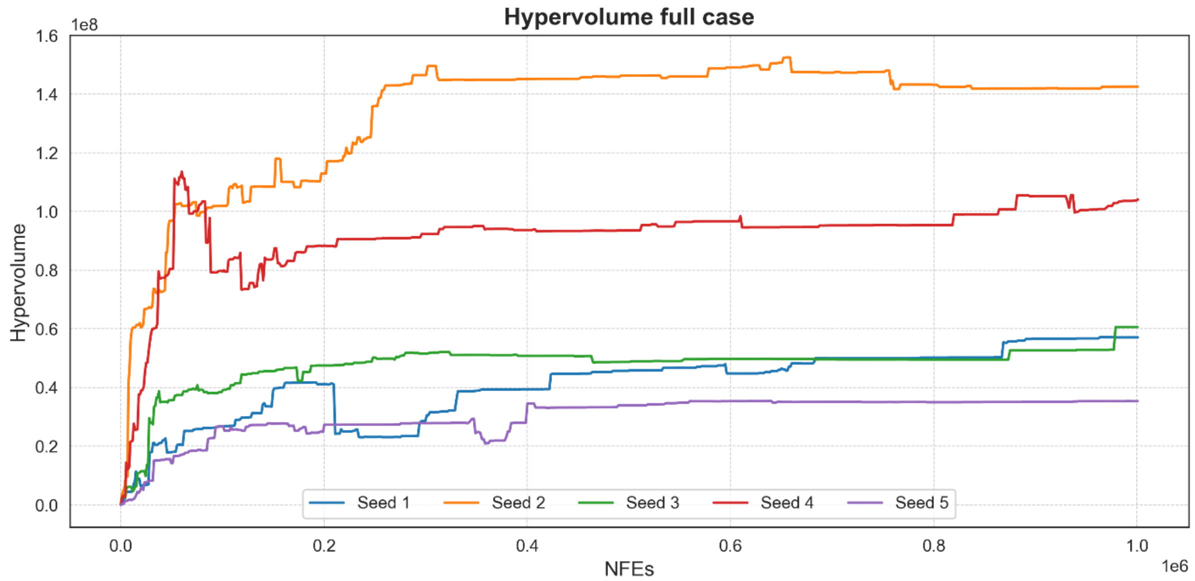

Figure 4-8: Hypervolume metric for full case (16 objectives). The full case was run for 1,000,000 NFEs over five seeds. The hypervolume shows unwanted behaviour, specifically noticeable for seed 4 between 0 and 100,000 NFE. The hypervolume peaks and does not reach that same height in the rest of the function evaluations.

4.3.2 Statistical analysis

The outcomes of the optimization process did not conform to a normal distribution, necessitating the use of non-parametric statistical methods. The Kruskal-Wallis test is a non-parametric statistical test used to determine whether there are statistically significant differences between two or more groups. A two-tailed Kruskal-Wallis test was therefore applied to assess whether there were significant differences between the medians of the three base objectives for the four different cases. The null hypothesis of the Kruskal-Wallis test is that all groups (base case, irrigation case, hydropower case, and full case) come from the same population (they have the same median).

Table 4-3: Results from two-tailed Kruskal-Wallis H test for each deficit type. The four cases are considered the groups. A significance level of 0.05 is applied.

	Hydropower deficit	**Environmental flow deficit**	**Irrigation deficit**
Test statistic (H)	77.492	38.340	46.830
p-value	1.058×10^{-16}	2.394×10^{-8}	3.778×10^{-10}

All three comparisons show strong evidence against the null hypothesis as the p-values are close to zero. This suggests that there are significant differences between the medians of the cases for each of the deficit types.

To further investigate, pairwise comparisons were executed by performing Dunn's test with Bonferroni correction. Dunn's test is a post-hoc test used after a Kruskal-Wallis test to determine which groups (datasets) differ significantly from each other. It provides a pairwise comparison between groups and adjusts for multiple comparisons (in this case, using the Bonferroni correction). For a full table of all the p-values, refer to appendix D.4. A summary of the results of the Dunn's pairwise comparison is:

- Hydropower deficits: Significant differences are mainly found between the base case and other scenarios, indicating that the base case differs significantly from the full, hydropower, and irrigation cases. The full case is significantly different from the irrigation case, but not from the hydropower case when it comes to the hydropower deficit.
- Environmental flow deficits: There are significant differences between the irrigation case and all other scenarios, indicating that the irrigation case stands out significantly in its impact on the environmental flow deficit compared to the others.
- Irrigation deficits: The base case differs significantly from the other cases. However, the irrigation, hydropower and full cases all do not differ significantly from each other.

5 Conclusion

This research has aimed to provide insight into the effects of objective disaggregation for the Pareto space of an Evolutionary Multi-Objective Direct Policy Search (EMODPS) simulation-optimization model. The study has used the Zambezi River Basin (ZRB) as a case study as it is a complex multi-reservoir system with competing objectives and a currently inefficient balance of water resource allocation for Water, Energy and Food (WEF). In the ZRB model this WEF nexus is at the core. The main research question "**How does the disaggregation of objectives influence the Pareto space in an EMODPS simulation-optimization model?"** has been answered by finding the answers to four sub-questions:

1. What is the baseline configuration of objective aggregation in the ZRB simulation-optimization model?

The baseline configuration of objective aggregation in the ZRB simulation-optimization model divides the objectives into three main categories in alignment with the WEF nexus: the hydropower production deficit representing the energy market, the irrigation deficit representing food security and environmental flow deficit at the Delta which functions as a proxy for the environmental health in the basin. There are five hydropower reservoirs in the ZRB model, which are aggregated as a non-weighted sum for the total hydropower production deficit. Additionally, eight irrigation districts are modelled and aggregated in a similar fashion. The irrigation deficit objective is normalized to prevent the great differences in irrigation diversion volumes to influence the solutions space extensively. These aggregations simplify the model, but may overlook specific impacts on individual reservoirs and irrigation districts. Besides these spatial aggregations, temporal aggregations can be observed in the base case. The temporal aggregations consist of the regular use of yearly averages. However, the use of these averages is considered a necessity as temporal disaggregation would require large amounts of detailed data that do not exist for the ZRB.

2. What are the impacts of the aggregations of objectives in EMODPS simulation-optimization models?

The aggregation of objectives in the ZRB model leads to a more streamlined optimization process, but it also obscures the distributional impacts of policy decisions. This can result in policies that favour overall system efficiency but may negatively impact specific communities or ecological areas. Aggregation tends to prioritize average outcomes over equitable distribution, potentially exacerbating existing inequalities and overlooking the needs of marginalized groups. The ZRB policies have this potential when high levels of aggregation are used for the development of reservoir policies. For example, the Cahora Bassa reservoir produces approximately 14.73 TWh/year in hydropower while the

Itezhi-tezhi reservoir produces around 0.675 TWh yearly. When aggregating these numbers into one objective, a deficit of 0.5 TWh/year would be acceptable, based on the scale of the Cahora Bassa production. However, this 0.5 TWh/year can mean the difference between having some power throughout the day, or having electricity once or twice a month in the Itezhi-tezhi region. The massive variance in the hydropower production and irrigation demands per region make a large difference when viewed individually, while they may be overlooked when only considering the bigger picture. Policies derived from aggregated models may thus inadvertently prioritize the needs of larger or more influential stakeholders at the expense of smaller or less visible ones.

In the case of the ZRB, the absolute overall resulting deficits are lower within the Pareto set of the aggregated base case. Although the disaggregation of solutions does provide valuable information about the trade-offs and effects of policies within the system, there are no observable negative consequences for the individual irrigation districts and hydropower reservoirs in the ZRB model, with a single exception.

3. How do varying levels of objective disaggregation affect the complexity and feasibility of the ZRB model?

In this research, four different levels of aggregation were selected to observe the effect on the Pareto space, the complexity of the optimization process and the feasibility of the model. Increasing levels of objective disaggregation heighten the complexity and decrease the feasibility of the ZRB model. As objectives are disaggregated, the number of variables and computations in the optimization problem increases, requiring greater computational resources to solve. The problem framings with 11 and 16 objectives both exhausted the available computational resources and required the research process to adapt accordingly. The hypervolume convergence metric shows convergence for all the bases, but still displays unexpected and unwanted behaviour after one million function evaluations. Additionally, visualizing and analysing such a large amount of data in a comprehensive and useful manner makes for quite a challenge, especially since the visualization techniques for higher dimensional solution spaces are limited. While the high number of objectives has made the model more complex and more challenging to solve, it has provides a more detailed and nuanced understanding of the trade-offs and impacts of different policies, potentially leading to insights that can aid in the decision-making process to come to more equitable and robust solutions.

4. How does the disaggregation of objectives modify the derived operating policies within the ZRB model framework?

The disaggregation of objectives in the ZRB model framework has a measurable effect on the operating policies within the Pareto set of solutions. The aggregated objectives of the base case have proven to result in a solution space with policies that generally cause better results through lower deficits for all the objectives. The disaggregation of objectives increased the average hydropower, irrigation and environmental flow deficits in most observations. Therefore, disaggregation is a very important tool that should not be overlooked, but from this research it cannot be concluded that disaggregating objectives has a positive effect by definition.

This research has concluded that to answer the main question on how the disaggregation of objectives influences the Pareto space in an EMODPS simulation-optimization model, modelling techniques and insights into the working and intermediate decisions made by the optimization and simulation processes is needed. There have been no clear trends or patterns visible when comparing the levels of disaggregation, the policies and the size of the irrigation districts and hydropower reservoirs. The effects of disaggregation have been significant. Although the effects have not been positive on the deficits in general, the process of disaggregating and more importantly, the practice of explicitly comparing different problem framings and levels of aggregation to increase equitability of release policies provides an addition to the transparency, and it provides the opportunity to optimize locally.

6 DISCUSSION

Before conducting the optimization and analysing the results, the expectation was that smaller irrigation districts and hydropower reservoirs would benefit from the disaggregation of objectives. By considering the deficits of each of these irrigation and hydropower locations as individual objectives, policies which benefit these smaller locations more were expected to be more frequently present in the Pareto set of solutions. The outcomes of the comparison between the highly aggregated base case and the disaggregated cases were not in line with this prior expectation. The cause of this unexpected finding is difficult to pinpoint but there are a few options to be mentioned. Possible explanations and other limiting factors of the research are discussed in 6.1. The suggestions for future research that follow, can be found in subchapter 6.2 and finally, the implications of the findings of this study are presented in section 6.3.

6.1 LIMITATIONS

A first possible cause of the unexpected results is the curse of dimensionality. Each of the disaggregated cases was optimized for a minimum of eight objectives. Due to these large numbers of objectives, the algorithm has to navigate a larger and more intricate solution space. It could potentially reach a local optimum or simply decrease in effectiveness, causing the MOEA to not function appropriately (Bechikh et al., 2017). Additionally, many-objective optimizations can show an increased sensitivity to modelling choices. It is therefore realistic to consider that the choice for the Generational Borg algorithm, the incorporation of the three base objectives in all the cases or the implementation of the RBFs caused the results to be less positive for the disaggregated cases.

Another limitation of this thesis is that of the available computational resources. As the optimization exploited the maximum amount of hours that could be sent to the supercomputer and it still had to combine multiple runs to compose some of the problem framings, the computational boundaries were found and stretched in this research. Having more resources in this regard would allow for more room in the optimization process to include more seeds, NFEs or calculations.

The lack of explicitly uncertain factors, such as hydroclimatic trends, impacts the robustness and validity of this research negatively. This research has not used an actually stochastic hydroclimatic model and it has not made use of scenarios to explore uncertain futures. These aspects would make great additions to the model and to science, to further explore the workings of the aggregation levels to improve distributive justice.

A final limitation of this research is the limited amount of similar researches and theories which could provide a foundation for this study. The very limited amount of research and literature on this topic make it nearly impossible to cross-reference the methods used in this research for their potential negative effect on the results. The transition from MOO to many-objective optimization will continue for the coming years and hopefully, future research will add more insight into the consequences of disaggregation.

6.2 Future research

The recommendations for future research using the ZRB model are divided into two sections, firstly the suggestions for future setups focus on how to use different settings to improve the knowledge that can be derived from the model about the impacts of objective disaggregation. Secondly, the additions to the ZRB model section discusses valuable additions to the model, for example by adding hydroclimatic uncertainties to the model.

6.2.1 Suggestions for future setups

Future research that builds upon this research directly, is advised to consider different setups by the use of different algorithms, the application or omission of aggregated objectives in disaggregated problem framings and by measuring the equitability of outcomes more explicitly.

Algorithms

When researching the effects of disaggregation on the ZRB again, it is recommended to apply various optimization algorithms, such as the (regular) Borg or the ε-NSGAII algorithm, to compare their performance with the Generational Borg algorithm. Observing changes in the hypervolume metric and the policies in the solution space could provide insights into their effectiveness.

Aggregated objectives

Another important recommendation is to exclude aggregated objectives from the disaggregated problem framings. Currently, the disaggregated cases include individual objectives for each hydropower reservoir and/or irrigation point, alongside the three aggregated objectives from the base case: the hydropower deficit, the irrigation deficit, and the environmental flow deficit at the Zambezi Delta. For future research, omitting the aggregated hydropower and/or irrigation objectives when including their respective disaggregated objectives may yield better optimization results. Including both aggregated and disaggregated objectives can potentially obscure the benefits of disaggregation.

6.2.2 Additions to Zambezi River Basin model

The ZRB model provides a lot of options for adaptations either by the modeller or by decision-makers. These options include a framework for changing the irrigation release policies, the addition of more irrigation districts or reservoirs, the use of dynamic stochastic hydroclimatic inputs, accounting for population growth and the use of ANNs for the parameterization of policies. Therefore, this ZRB model is very qualified to investigate these aspects and their effects on the solution space. For example, adding stochastic hydroclimatic inputs would greatly affect the robustness and validity of the solution space. The model contains a setup to incorporate a rainfall-runoff model calibration (HBV). Additionally, the necessary data to account for population growth and its effect on the irrigation and hydropower demands is present in the model and can be used to improve the model's validity.

Using these elements, intergenerational justice could also be explored for the ZRB. This research has focussed on spatial intragenerational justice by looking for more equitable ways of modelling. Although this topic itself also has plenty of room for exploration, the future scenarios of the ZRB are alarming and do require considerable thought for the future generations and the ecosystem, which is of global importance.

6.3 IMPLICATIONS

The aggregation levels of objectives have proven to change operating policies for better or for worse. When observing the relation between the magnitude of the demand, albeit for irrigation or for hydropower, and the aggregation of objectives, the effect of the aggregation levels appear to be smaller for larger districts. This does mean that medium-sized and small areas have a heightened sensitivity to the level of objective aggregation. In areas where there is an ongoing deficit, it is essential to take those points in the system with smaller demands into account. Within the ZRB there are millions of people who are fully dependent on the water from the basin and as water use for irrigation and hydropower increases, the livelihoods of these people must remain a priority. In the grand scheme of development, energy, industry, tourism and corporations often take priority when it comes to the allocation of resources. In the ZRB, many people have protested against the development of new hydropower reservoirs because displacement and access to power are big issues for the local inhabitants (*The Zambezi River basin a multi-sector investment opportunities analysis*, 2010). The incorporation of stakeholder input, smaller irrigation districts and reservoirs in the initial development of the ZRB model have definitely had a positive influence on the policy recommendations and effectiveness of the model (Castelletti, 2019). As the stakes get higher and water becomes more scarce during droughts, and floods are becoming more frequent during raining seasons, the explicit consideration for distributive justice and aggregation choices should be a staple in every reservoir optimization model.

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8 APPENDICES

APPENDIX A: IRRIGATION DISTRICTS

The irrigation districts in this research can be considered as the actors/stakeholders, as the human stakeholders hold great interest in the irrigation diversion volumes. The sub-basins in the system are based on HydroSHEDS pfaffstetter level 5. The irrigation district IDs in the appendix are the IDs used in the model, which means that they are *i*+1 of the IDs used in the report.

Table 8-1: Irrigation districts overview. The ID refers to the IDs in the modelling code. In this thesis, the ID's range from 1 through 8.

Irrigation district	**ID**	**Sub-basin**	**Target demand [m³/sec]**	**Ranking, largest to smallest**
Batoka Gorge	2 (1)	12279 & 12278	7.24	5
Kariba	3	12271 & 12272	19.11	4
ITT	4	12261	36.42	2
KGL	5	12261	3.59	6
Kafue-Zambezi	6	12250	100.08	1
CB	7	12235 & 12233	0.05	8
MN	8	12231	1.74	7
Shire-Zambezi	9 (8)	12210	31.31	3

APPENDIX B: UML CLASS DIAGRAM

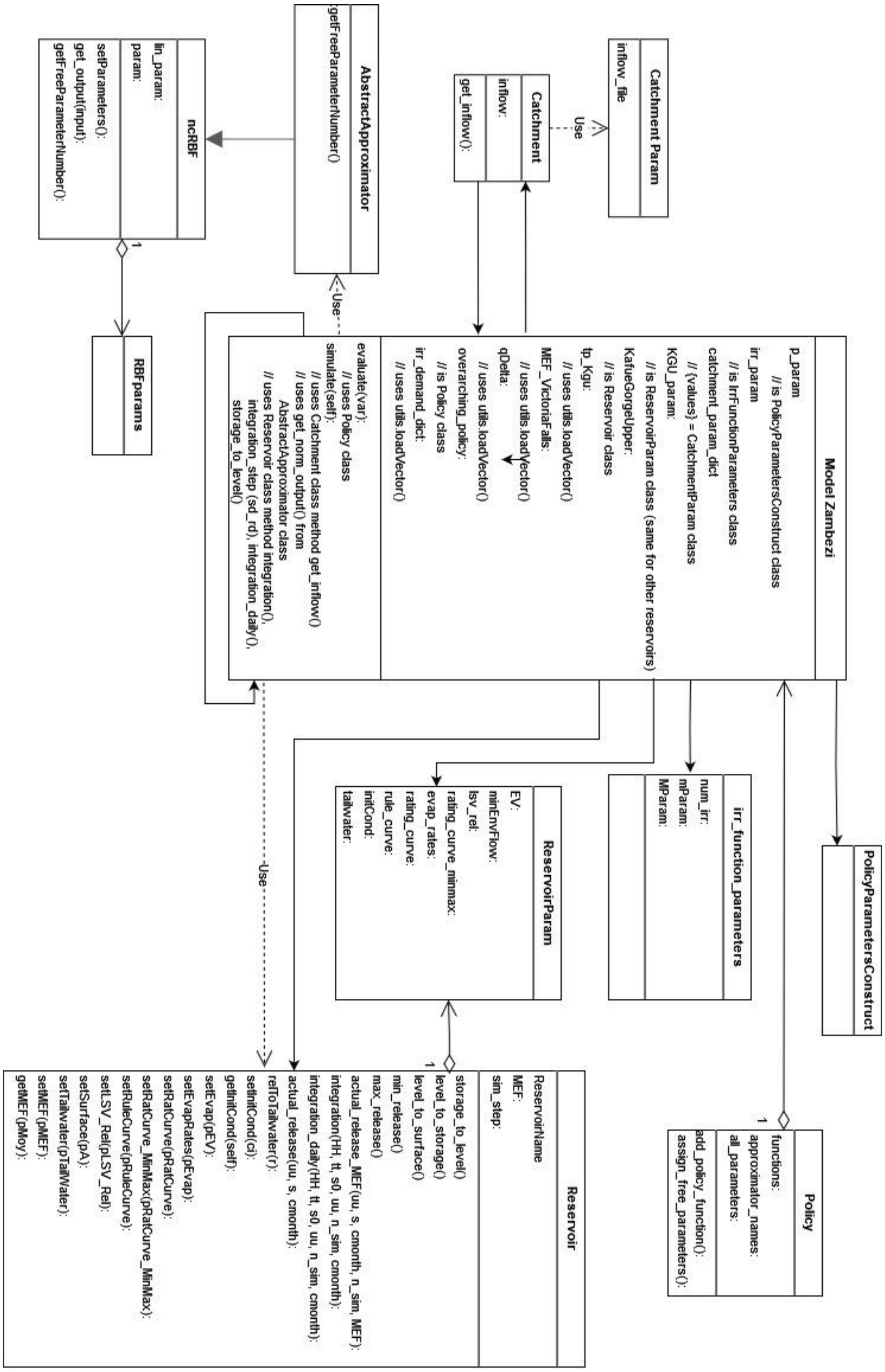

Figure 8-1: UML diagram. The Utils class is not represented in the diagram, because it is used by nearly every class, to retrieve information from data files. A selection of other classes is represented here based on whether they are in use during this research and their relevancy for the essential classes in the model.

APPENDIX C: SETTINGS

C.1 RBF settings

Table 8-2: RBF settings. Full table, including data type and label in model.

Parameter Name	**Value**	**in Python**	**Data Type**
Name	release	name	str
Type	ncRBF (non-convex)	type	str
Number of Inputs	7	n_inputs	int
Number of Outputs	5	n_outputs	int
Number of RBFs	11	n_structures	int
Max Input	[5883000000.00,1178000000.00,180798000000.0000,51704000000.00000,62840000.00,12,11213.5790]	max_input	np.array
Max Output	[7338.28210,2894.4600,11539.93658041603,15859.69558599696,4445.967529173009]	max_output	np.array
Min Input	[699000000.0,5000000.0,116054000000.0000,32000000.0,10950000.0000,1,0]	min_input	np.array
Min Output	[0,0,0,0,0]	min_output	np.array

Appendix D: Results

D.1 3D plots

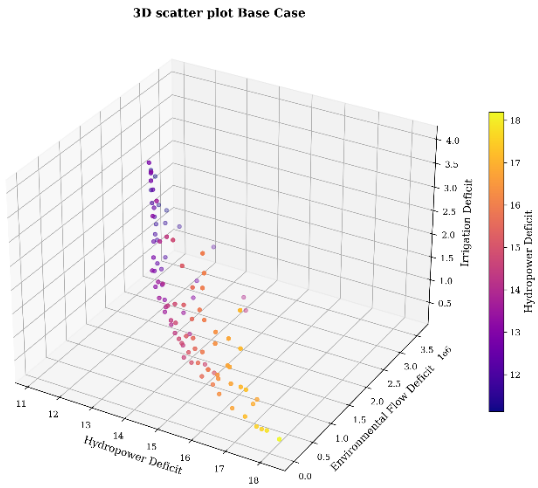

Figure 8-2: 3D plot Base case

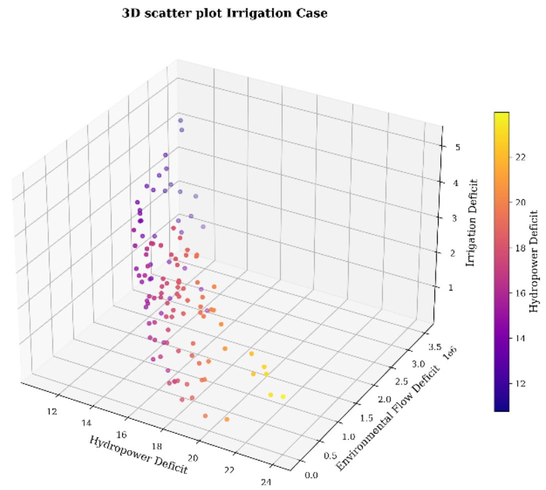

Figure 8-3: 3D plot Irrigation case

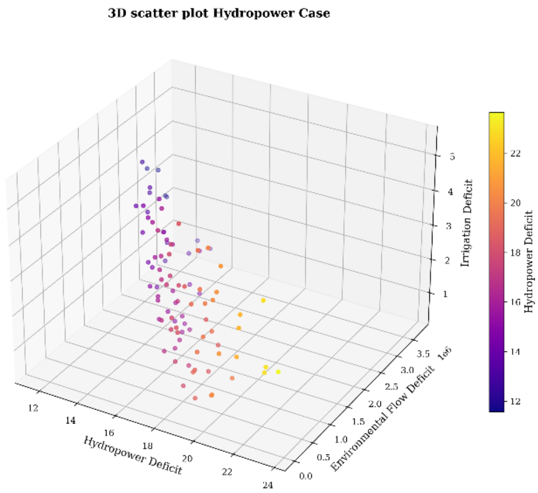

Figure 8-4: 3D plot Hydropower case

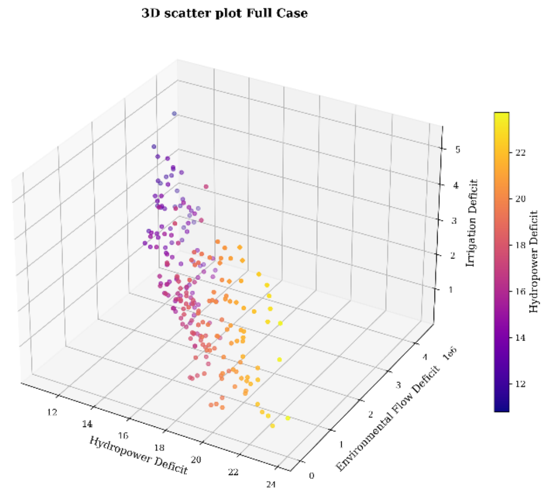

Figure 8-5: 3D plot Full case

D.2 Parallel axis plots

Three base objectives: hydropower deficit, irrigation deficit and environmental flow deficit

The coloured lines in the parallel plots in figure 8-6 represent the best solution for the hydropower deficit, the best solution for the environmental flow deficit, and the best solution for the irrigation deficit from the Pareto set of solutions. The desired value of these deficits is zero, indicating that the direction of preference is downward and the best solutions are those with the lowest values for an objective.

In some instances, multiple solutions were identified as the 'best' because they achieved zero deficit values. In such cases, the solution with the lowest sum of deficits across all objectives was selected as the 'best.' This approach ensures that the selected solutions are balanced and minimize overall deficits across the different objectives.

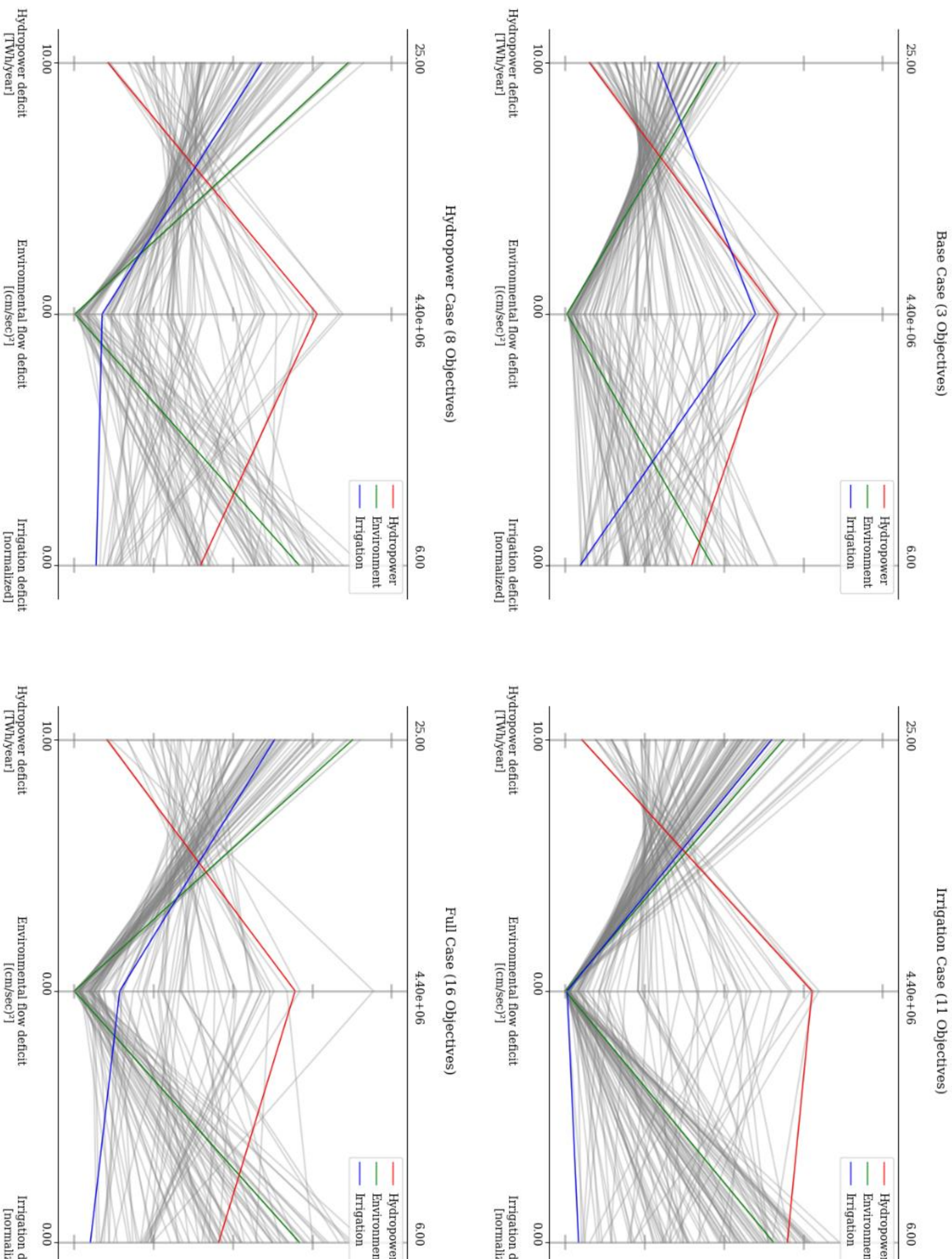

Figure 8-6: Parallel axis plots of the base case (optimized for three objectives), irrigation case (optimized for 11 objectives), hydropower case (optimized for eight objectives) and full case (optimized for 16 objectives) with normalized lower and upper bounds based on the minimum and maximum values across the cases. Only the three base objectives are shown with their best solutions to accommodate comparison and simplicity. The direction of preference is downward.

Parallel axis plots per case

The parallel axis plots for the irrigation case are shown in figures 8-7 and 8-10. The plot which highlights the smallest and largest irrigation district (figure 8-10) is shown in a later segment to allow for comparison with the smallest and largest hydropower reservoirs in the hydropower case (figure 8-10) and in the full case (8-11). The same accounts for the hydropower case (figures 8-8) and the full case (figure 8-9).

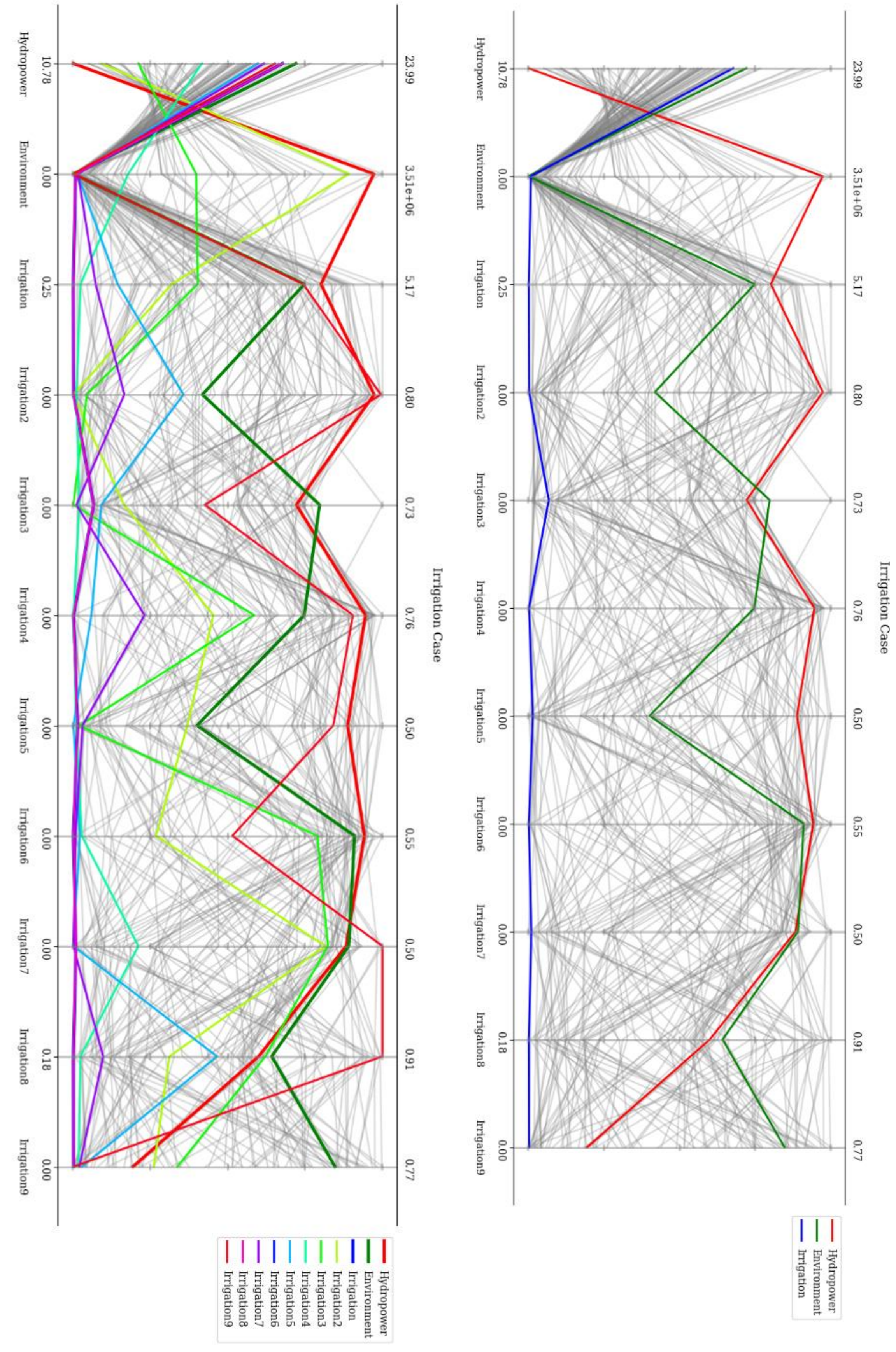

Figure 8-7: Irrigation case parallel plots. The graph on the left shows all the 'best solutions' for each of the 11 objectives, the graph on the right only highlights the 'best solution' of the three base objectives

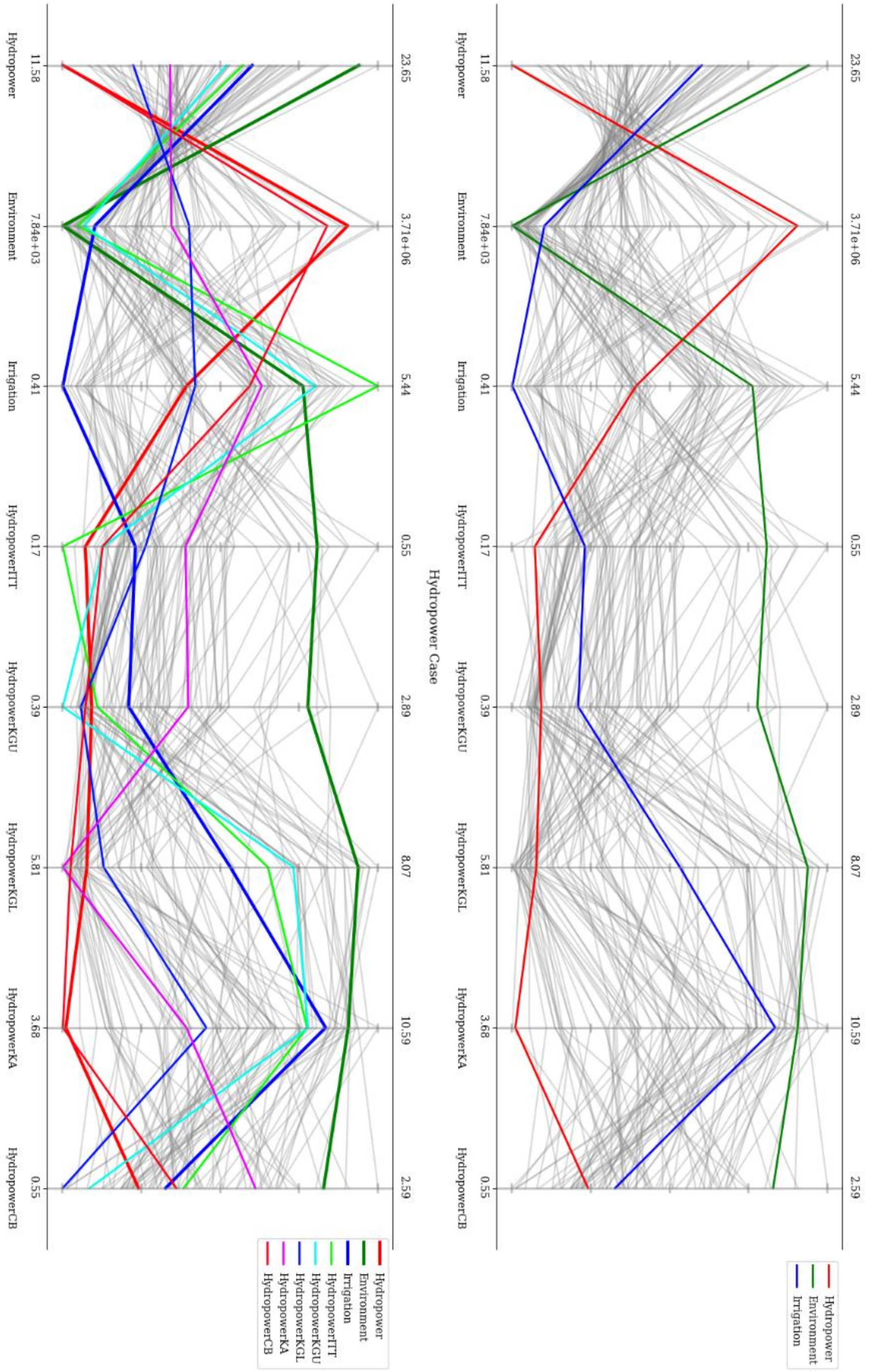

Figure 8-8: Hydropower case parallel plots. The graph on the left shows all the 'best solutions' for each of the eight objectives, the graph on the right only highlights the 'best solution' of the three base objectives

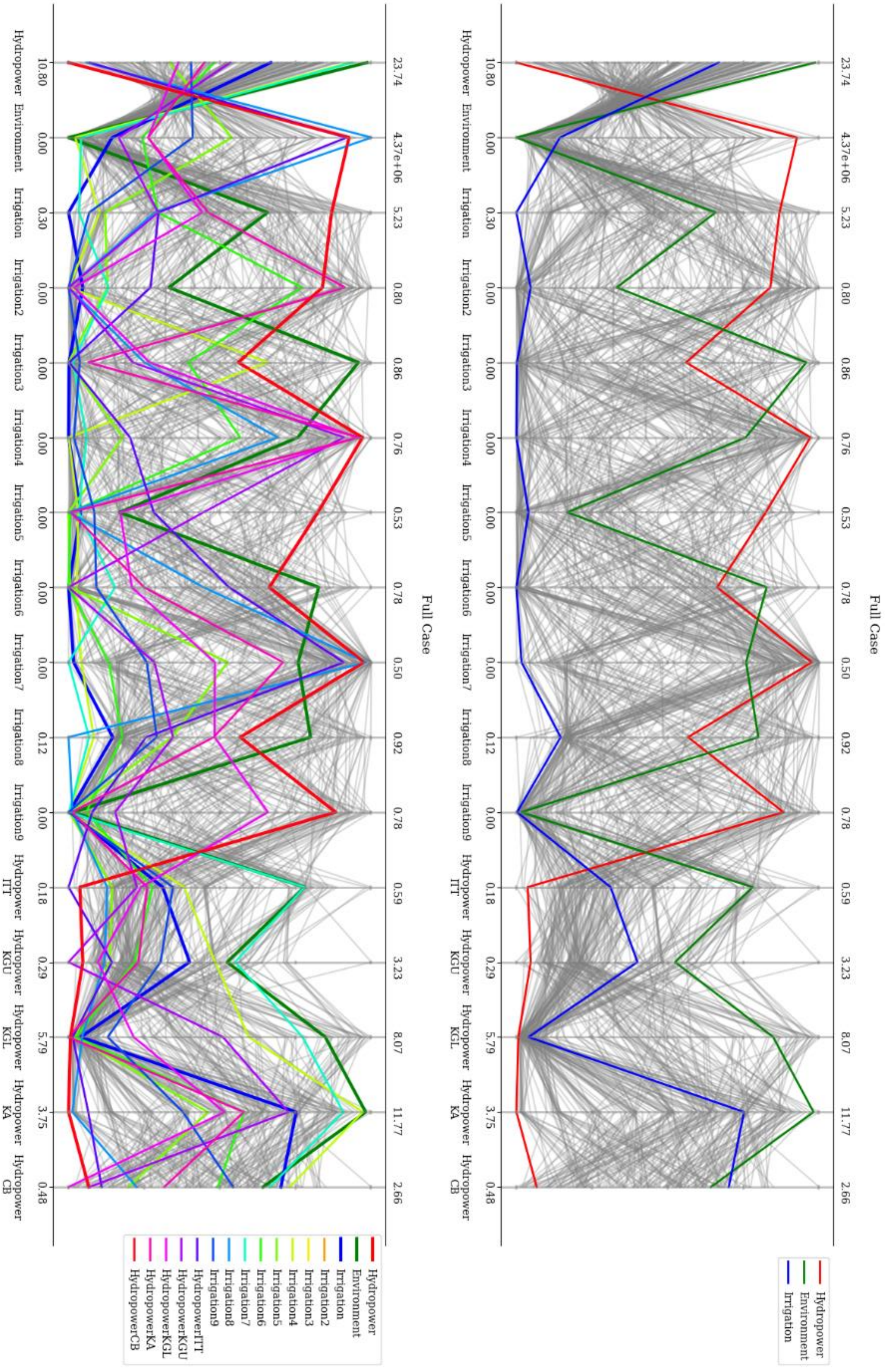

Figure 8-9: Full case parallel plots. The graph on the left shows all the 'best solutions' for each of the 16 objectives, the graph on the right only highlights the 'best solution' of the three base objectives

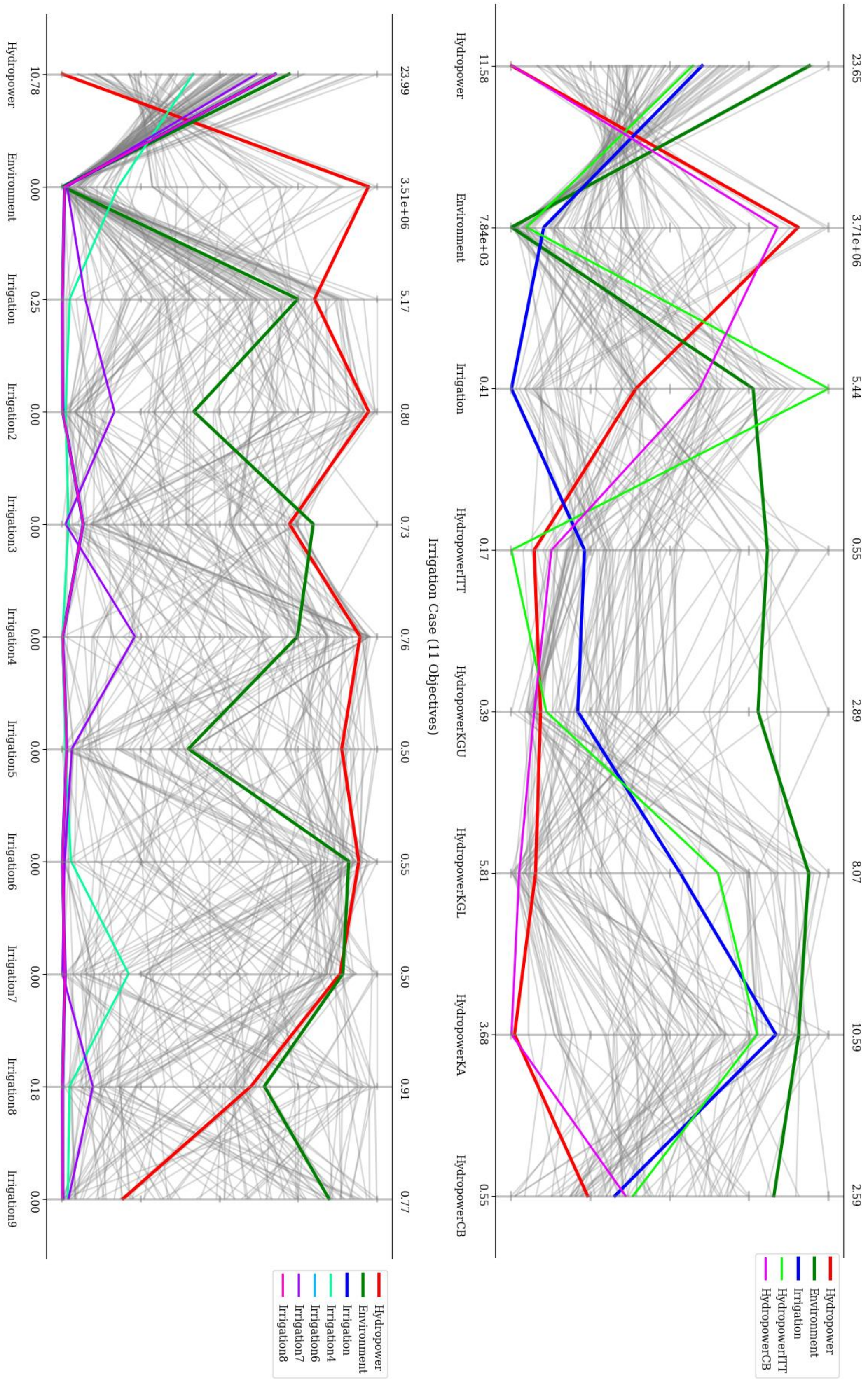

Figure 8-10: Parallel axis plots for the hydropower and irrigation cases, highlighting the smallest irrigation districts (7 and 8) and the largest irrigation districts (6 and 4). For the hydropower case, the largest reservoir (CB) and the smallest reservoir (ITT) are highlighted.

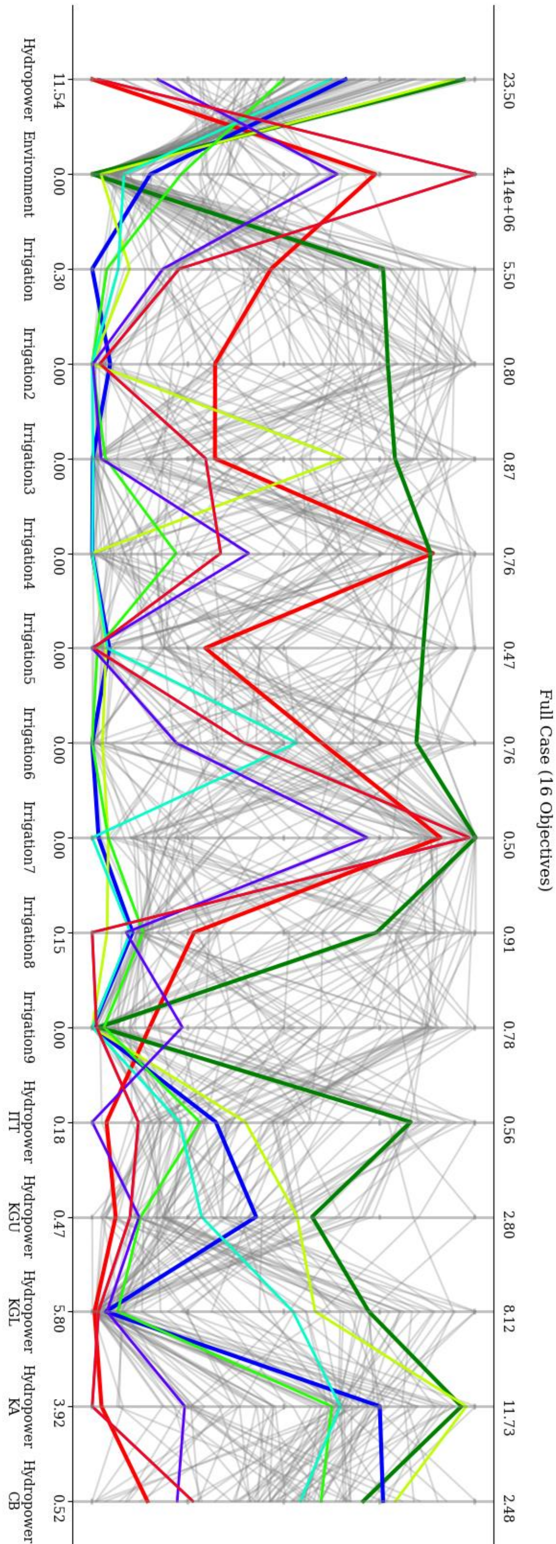

Figure 8-11: Parallel axis plot for the full case with the two smallest and largest irrigation districts and the smallest and largest hydropower reservoirs highlighted.

D.3 Monthly irrigation deficits

For the monthly deficits, the average actual (non-normalized) irrigation deficit per month is displayed in the graphs in figures 4-5 through 4-10.

Largest irrigation districts

First, the largest irrigation district 6 and the second largest district 4 are discussed by viewing the monthly irrigation deficits per 'best solution' per case in [m³/sec].

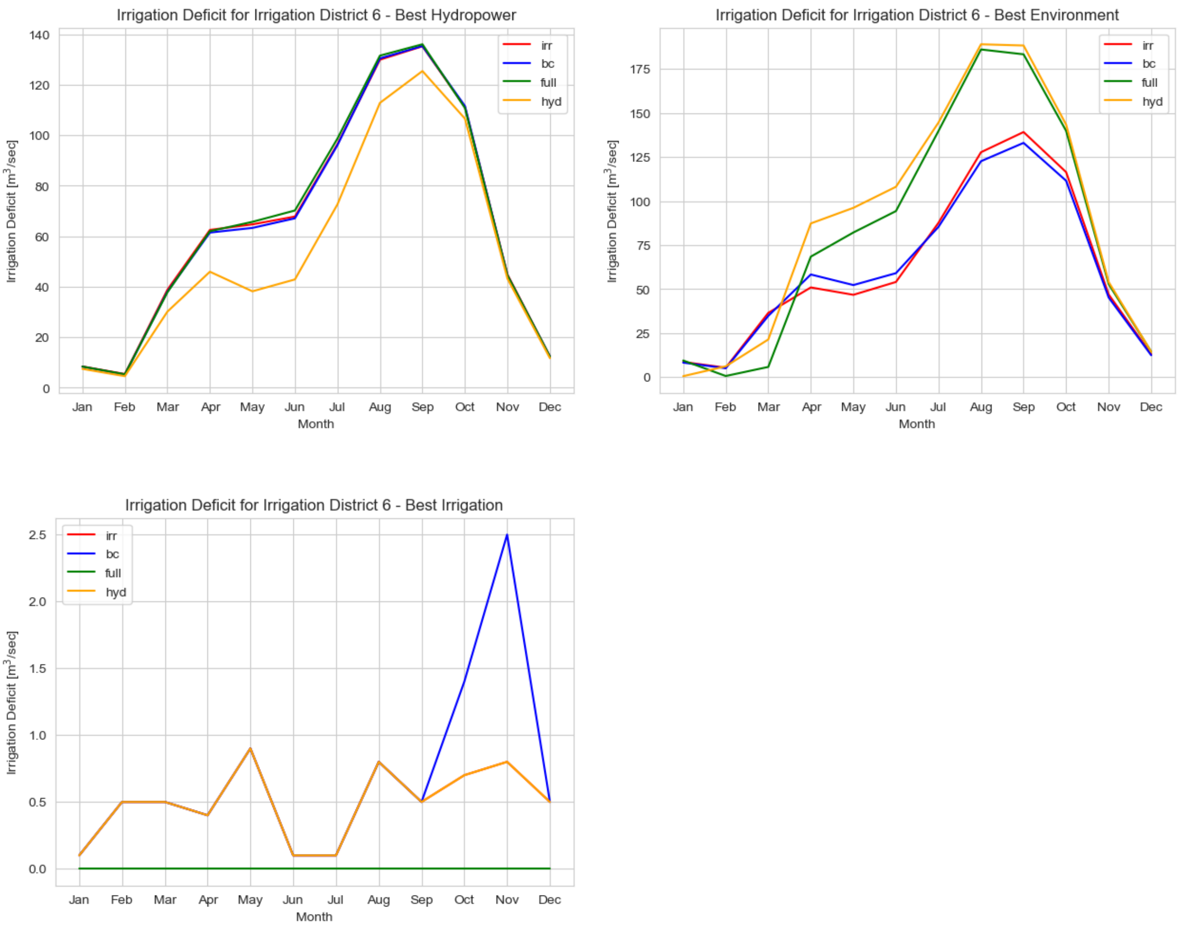

Figure 8-12: Monthly irrigation deficits for irrigation district 6 (largest district) for the best solutions to the three base objectives: best hydropower, best environmental flow and best irrigation solutions. Each of the four cases is shown in the graphs with a different colour.

For irrigation district 6, the district with the highest target demand for irrigation in the basin, there are visible differences between the different levels of aggregation, most prolific in the best environment (figure 4-6) and the best irrigation solution (4-7). For the best hydropower solution, the hydropower case is the only one that deviates from the other cases with a smaller irrigation deficit. This is an interesting observation, as one would expect the hydropower case to be less advantageous for the irrigation deficits. Another noticeable difference between the levels of aggregation is that the full disaggregation case (16 objectives) does not cause a deficit for irrigation district 6 when the best irrigation solution is selected, while the hydropower solution has a (near-) equal deficit to the hydropower case. The base case negatively stands out when looking at the best irrigation solution for the largest district in the model.

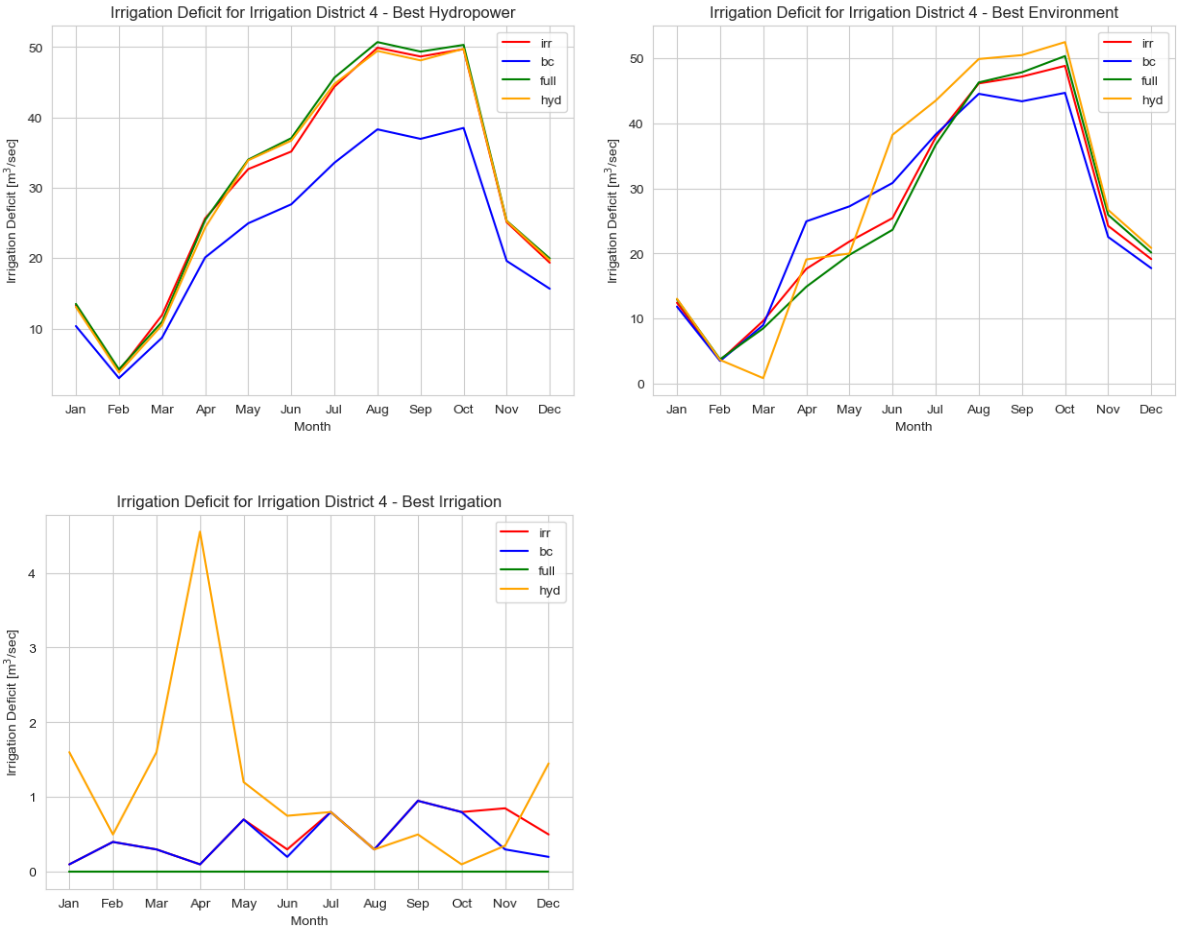

Figure 8-13: Monthly irrigation deficits for irrigation district 4 (second largest district) for the best solutions to the three base objectives: best hydropower, best environmental flow and best irrigation solutions. Each of the four cases is shown in the graphs with a different colour.

For irrigation district 4 the base case has a smaller deficit than the other cases when it comes to the best hydropower solution out of the Pareto set of solutions. For the best environmental flow solution, on average over all the months, there does not appear to be a significant difference. The hydropower case does have a very notable effect on the irrigation deficit in district 4 when selecting the best irrigation case.

Smallest irrigation districts

Figure 8-14: Monthly irrigation deficits for the two smallest irrigation districts 7 (smallest) and 8 (second smallest) for the best solutions to the three base objectives: best hydropower, best environmental flow and best irrigation solutions. Each of the four cases is shown in the graphs with a different colour.

The graphs for irrigation district 7 appear to be difficult to draw conclusions from at the first glance, considering the harsh transitions. However, when realizing that considering this small district size and irrigation demand, relatively small irrigation deficits in absolute terms may have great consequences as there is a very limited availability of irrigation water anyway. The relative deficits, discussed later in this chapter, will go more in dept about the implications of these deficits. The hydropower case has the highest deficits as a consequence for the smallest district in the system.

Irrigation district 8 has the second smallest irrigation demand in the ZRB model. The base case ‘scores’ relatively well for this irrigation district, when the expectancy was that the base case would cause a higher deficit for the smaller districts. Especially for the best hydropower solution, it can be observed that the Pareto-front contains hydropower solutions that are more damaging to the district’s irrigation diversion volume than the disaggregated cases.

D.4 Statistical analysis

The bold p-values indicate significance with a significance level of 0.05.

Post-hoc Dunn's test results for Hydropower:

Table 8-3: Post-hoc Dunn's test results for Hydropower

	BC	**Full**	**Hyd**	**IR**
BC	1.00E+00	**2.31E-16**	**1.11E-08**	**4.51E-09**
Full	**2.31E-16**	1.00E+00	1.13E-01	**4.73E-02**
Hyd	**1.11E-08**	1.13E-01	1.00E+00	1.00E+00
IR	**4.51E-09**	**4.73E-02**	1.00E+00	1.00E+00

Post-hoc Dunn's test results for Environmental flow deficit objective:

Table 8-4: Post-hoc Dunn's test results for Environmental flow deficit

	BC	**Full**	**Hyd**	**IR**
BC	1.00E+00	7.31E-01	1.00E+00	**1.00E-06**
Full	7.31E-01	1.00E+00	5.48E-01	**2.15E-03**
Hyd	1.00E+00	5.48E-01	1.00E+00	**1.00E-06**
IR	**1.00E-06**	**2.15E-03**	**1.00E-06**	1.00E+00

Post-hoc Dunn's test results for Irrigation deficit objective:

Table 8-5: Post-hoc Dunn's test results for Irrigation deficit

	BC	**Full**	**Hyd**	**IR**
BC	1.00E+00	**4.86E-07**	**2.06E-06**	**4.06E-09**
Full	**4.86E-07**	1.00E+00	1.00E+00	1.00E+00
Hyd	**2.06E-06**	1.00E+00	1.00E+00	1.00E+00
IR	**4.06E-09**	1.00E+00	1.00E+00	1.00E+00