ROBUST WATER RESOURCE PLANNING AT RIVER BASINS

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Abstract

Robust Water Resource Planning at River Basins

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Freshwater is a fundamental, but scarce resource vital for life. Uncertainty is one of the significant factors in water resource systems planning and management problems. We consider the problem of water resource systems planning at river basins when there are competing demands and different operating policies. Firstly, we provide a mathematical model using the minimum cost network flow problem, in which the system is represented as a directed multi-graph. Arc coefficients are introduced for modeling gain/loss in the system. Multiple arcs are used to create of the system priorities. Secondly, we reformulate the aforementioned problem using cardinality-constrained robust optimization to address uncertainty when there is an agreement amongst decision makers about uncertainty sets. A set of experiments is conducted to demonstrate the trade-off between the level of robustness and the cost of robustness. We also use Monte-Carlo simulation to analyze the performance of the model in terms of its feasibility in the presence of uncertainty. Thirdly, we employ robust decision making (RDM) to address uncertainty when there is not an agreement amongst decision makers. RDM is applied to analyze the system performance under evaporation/precipitation uncertainty. Monte-Carlo simulation is used to take samples from the uncertain future ranges. To evaluate the policies multiple attribute decision making (MADM) methodology is used. We have shown that the combination of RDM and MADM is a suitable approach for dealing with deep uncertainty and selecting the most suitable robust strategy. This thesis provides insight into modeling uncertainty in river basins systems.

To my beloved Mom & Dad and my dear wife, Mina

for their love, endless support and encouragement

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Chapter 1

Introduction

The main premise of this thesis is that uncertainty is an important factor in water resource management problems. To address uncertainty, we use two methodologies, namely robust optimization and robust decision making. We show that:

- robust optimization is an effective method for solving water resource planning problems when there is agreement about the uncertainty sets among decision makers,

- robust decision making is an effective method for solving water resource planning problems in the case of deep uncertainty and lack of agreement among decision makers about the uncertainty sets. We also show that multiple attribute decision making is an effective tool for evaluating alternatives when robust decision making methods are applied.

To our knowledge, this thesis is the first work that uses robust optimization in a water resource planning problem in which the network is represented by multiple arcs. In addition, to our knowledge, this work for the first time combines robust decision making and multiple attribute decision making methodologies in a water resource planning problem when there is a lack of agreement amongst decision makers; and it provides a new perspective for water resource planning problems under deep uncertainty that require selection of a decision amongst a set of alternatives.

1.1 Motivations

Freshwater is a fundamental, but scarce resource vital for life. It might seen abundant; however, only 3% of the water on earth is freshwater [95], while the remainder is saltwater located in oceans. In addition, some two-thirds of this freshwater is placed in glaciers and permanent snow cover [167]. Furthermore, there is an inextricable connection amongst water, development, culture, economy, energy, industries, and food. This scarce resource is unevenly distributed in time and space. There are some factors, such as climate change, an increasing population, fast urbanization, and migration that have led to overexploitation of water resources [183, 184, 199]. While the water supply remains constant the world population is growing and the demand for freshwater is increasing. This resource has been mismanaged for many years and has been used unsustainably. Consequently, it is not surprising that first of the top ten global risks in terms of impact is the water crisis [1]. Based on a recent article published in *OR/MS-Today* [160], water problems constitute one of the engineering grand challenges – and operations research is a catalyst for resolving them. Following this view, this thesis provides an illustration of the potential of several operations research methods in solving water resource system planning problems under uncertainty. In more detail, the motivations for the work presented in this thesis are:

- **The need for effective methods for solving water resource systems planning problems under uncertainty**
  All water resource systems planning problems are influenced by uncertainty. Thus, it is essential to take this aspect of the problem into account when building mathematical models of these problems. In this thesis, we use robust optimization to mathematically model and solve a water resource planning problem. This approach provides a solution that is feasible for any realization of the uncertainty in a given set.

- **The need for effective methods for solving water resource systems planning problems under condition of deep uncertainty**
  Uncertainty is inevitable in water resource systems planning. In some planning problems decision makers have to contend with condition of deep uncertainty, in which not only the future state of the system is not clear but also there is no agreement about it. Therefore, it is crucial to take this facet of the problem into

consideration when building mathematical models of these problems. In this thesis, we use robust decision making and multiple attribute decision making to cope with deep uncertainty.

1.2 Thesis overview

In Chapter 2 of this thesis, the necessary background for the work presented in this thesis is provided. The chapter commences by discussing water resource systems management in general, and is divided into. This section includes three main subsections: water resource systems definitions and characteristics, water resource management problems, and an overview of water resource management approaches. We also describe deep uncertainty and lack of agreement in the subsection called water resource systems definitions and characteristics. Next, we survey the problem of interest, which is water resource systems planning and management at river basins. Further, two methodologies of choice are elaborated. First, robust decision making approach [114] is explained in detail as a decision making tool for condition of deep uncertainty and lack of agreement among decision makers. Second, cardinality-constrained robust optimization [20], one of the main operations research methods employed in this thesis, is described. The robust optimization (RO) approach provides an optimal solution that is feasible for any realization of the uncertainty in a given set.

Chapter 3 provides a deterministic mathematical model for management of river basins. The model is demonstrated via an artificial river basin system. A number of different experiments are designed to show the behavior of the model under different situations. To address future uncertainties, we test the model performance under the effect of shift in the timing of the annual peak of flows in the water system.

In Chapter 4, we employ robust decision making (RDM) [111] to analyze performance of the same water resource system as in Chapter 3 under evaporation/precipitation uncertainty. Monte-Carlo simulation is used to take samples from the uncertain future ranges. To evaluate the policies multiple attribute decision making (MADM) is used. We show that the combination of RDM and MADM is a suitable approach for dealing with uncertainty and selecting the most suitable robust strategy.

In Chapter 5, the robust water resource planning model applying cardinality - constrained robust optimization is developed. We design a set of experiments for the same water resource system as in Chapter 3 to test the robust model. Monte-Carlo simulation is used to analyze the performance of the model in terms of its feasibility in the presence of uncertainty. We show that the robust model can protect the decision maker against uncertainty, and thus that robust optimization is an effective modeling approach for dealing with uncertainty when modeling management of river basins.

Chapter 6 concludes this thesis by re-stating its main contributions and suggesting some areas for future work.

1.3 Summary of contributions

First, we provide a clear procedure to mathematically model a river basin water resource allocation problem when there are competing demands and different operating priorities. Specifically, we define a mathematical model which is a minimum cost network flow problem in which the system is represented as a directed multi-graph. Multiple arcs are used in order to develop a piecewise linear approximation of the cost function.

Second, we employ RDM when there is a condition of deep uncertainty and there is no agreement regarding future states of the system. MADM is used for evaluation of the alternatives using identified performance metrics in RDM methodology. The combination of RDM and MADM provides a systematic evaluation procedure for decision makers in the process of selecting the most robust strategy.

Third, we use RO to address uncertainties when there is agreement about the uncertainty sets. Specifically, cardinality-constrained robust optimization is used for the water resource planning problem. The cardinality-constrained robust optimization model provides the option of controlling the level of robustness of the solution in terms of feasibility in against the cost of such a robust solution in the presence of uncertainty.

Chapter 2

Literature review

This section provides an overview of the main topics in water resource systems planning and management. This chapter is divided into four different sections:

(1) Section 2.1 - General water resource systems management

(2) Section 2.2 - Problem of interest: water resource planning and management at river basins

    (1) 2.2.1 - Linear models in planning and management of river basins

    (2) 2.2.2 - Computer based software models

(3) Section 2.3 - Methodologies of choice:

    (1) 2.3.1 - Robust decision making

    (2) 2.3.2 - Cardinality constrained robust optimization

(4) Section 2.4 - Summary

2.1 General water resource systems management

In brief, gathered here are definitions of water management, water resource systems management, water resource planning and applications of water resource management projects.

Freshwater, which is a precious resource, is not equally distributed in time and space; so it has to be managed. Water management is defined by different authors as follows:

– Water management is defined as "the control and movement of water resources to minimize damage to life and property and to maximize efficient beneficial use"[185].

– "Water resources systems management is an iterative process of integrated decision-making regarding the uses and modifications of waters and related lands within a geographic region" [168, p. 150].

– "It includes the traditional activities of water resources engineering: planning, design, maintenance and operation of the water-related infrastructure"[167, p. 50].

– "Water resources planning and development is concerned with modifying the time and space availability of water for various purposes so as to accomplish certain basic national, regional and local objectives. In most cases, the ability to achieve these objectives is limited by the non-uniform availability of water and other resources"[90, p. 19].

– "Water resources management refers to a whole range of different activities: monitoring, modeling, exploration, assessment, design of measures and strategies, implementation of policy, operation and maintenance, and evaluation"[158, p. 2].

Considering all the above definitions water resource systems management encompasses planning, developing, distributing, controlling, maintaining, and managing of water resources and their related infrastructures to optimize the utilization of water.

Water management issues encompass global, national, regional, and local levels and decision scales include strategic, tactical, and operational. Water planning activities are commonly costly, capital-intensive, engage few to many users with wide-ranging objectives, and require approval from politicians and governments. Water management problems are diverse and ubiquitous, including trans-boundary river basin management, water supply and distribution design, water network operation planning, water distribution network expansion, reservoir scheduling, flood control, water pollution control, water treatment, wastewater reuse, etc.

2.1.1 Water resource systems definitions and characteristics

The Encyclopedia Britannica defines *water resource* as: *"any of the entire range of natural waters that occur on the Earth, regardless of their state (i.e., vapor, liquid, or solid) and that are of potential use to humans"* [144]. Surface water and groundwater are the two fundamental sources of water. However, in some arid regions desalination is used for obtaining drinking water.

Water resources are systems composed of a set of water resources elements linked by interrelationships into a purposeful whole. For instance, a water supply reservoir for a small town, linked with a water distribution network, would constitute a water system. The elements of a water resource system can be either natural (rivers, lakes, glaciers, precipitation, ground water, etc.) or artificial (reservoirs, weirs, channels, hydroelectric power plants, barrages, pumping stations, etc.). The relationships between the elements are either real (e.g., water diversion) or conceptual (e.g., organization, information, etc.) [90, p. 30]. "Water resource systems are "open systems", i.e., their elements interact with the environment of the system." [186, p. 38].

Some of the most important characteristics of water resource systems that makes managing them challenging are the following:

Uncertainty Generally speaking, uncertainty is the state of having imperfect or limited knowledge regarding a situation, prediction, information, etc. For example, uncertainty can be seen in the form of data errors in real-life applications due to implementation errors or measurement/estimation errors [66]. Ling in 1993 [117] provides a classification for sources of uncertainty in water management. He states that there are two main forms of uncertainty: (1) variability, and (2) ambiguity. The first form is a result of physical characteristics (i.e., inherent stochastic variability) of water systems [162]. The second form is due to a lack of understanding or limited knowledge. Both sources are rooted in lack of clarity and ignorance owing to lack of data, lack of detail, behavior of the system, lack of structure for framing the problem, etc. Simonovic in 2012 [168, p. 132] provides an updated taxonomy of sources of uncertainty in water resource management (see Figure 1). For more details we refer the reader to [168, 167, 117, 162].

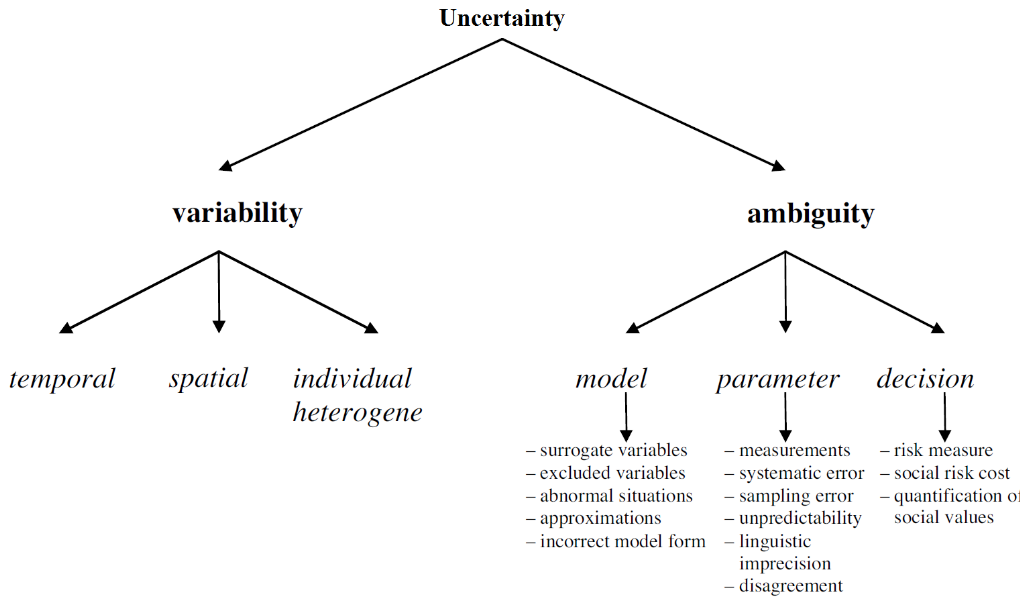

Figure 1: Sources of uncertainty in water resources systems management (adapted from [179])

In order to find a way to deal with uncertainty, one needs to distinguish different levels of uncertainty. Stein and Stein [172] define *shallow uncertainty* as a situation in which the probabilities of outcomes are reasonably well known. In such situations, past events provide valuable insight into the future ones. For instance, in water resource systems planning problems decision makers use models to forecast future states of a water system using past data (i.e., future water demand, future water supply, etc.). Due to the complexity of managing water resources, mathematical modeling is required. In contrast, Knight in 1921 [100] defines "Knightian" uncertainty as a condition when there is no probabilistic information available to characterize some aspects of a problem. Under this condition, the most likely realization of a problem is unknown [130]. Similar to "Knightian" uncertainty, Lempert et al. in 2003 [111], define *deep uncertainty* as a condition in which "decision makers are not aware or cannot reach an agreement on (1) the appropriate models to describe interactions among a system's variables, (2) the probability distributions to represent uncertainty about key parameters in the models and/or, (3) how to value the desirability of alternative outcomes". This happens when there are multiple possible models with poorly known parameters because we do not have enough knowledge about the system or the system has essentially unpredictable elements [172]. For more detailed information on different levels of uncertainty the reader is referred to [187].

Water-food-energy nexus The nexus term was first coined through Bonn Conference in 2011 [82] with the aim of increasing water, energy and food security. Water has a central role in the nexus. Water is inseparably connected with food and energy. Drinking water is the first and the basic usage of water. We use water for agriculture to produce food. According to Zeitoun [201], more than 80% of global water is consumed in irrigated crop production. Water is linked with energy too. We use water to support power generation either directly for hydropower or cooling thermal power stations. Electricity, as an energy obtained from water, is applied for cooling homes or heating food. Water is coupled with urbanization and industrialization. Almost any product needs water in one of its production process. As more people are expected to live in urban areas in the future, more water, food, and energy will be needed in cities. The ecosystem is dependent on water as well. Considering the aforementioned facts, one concludes that actions in one sector have an impact on one or both other sectors. It is also worth mentioning that using integrated models that can represent the nexus in a mathematical form is important.

Large scale systems Water resource systems are inherently large scale systems. In such cases, the problem of either choosing a component or not is challenging owing to many configurations for constructing a model. Large-scale systems problems are not just the small-scale systems problems magnified [70]. In such situations, using the same modeling approaches that are used for small-scale systems might not be practical for large scale ones. Moreover, the system consists of many subsystems and modeling subsystems and connecting the models to understand the large system behavior cannot be a good solution. Furthermore, large scale systems interact with outside and defining a boundary is another issue since total independence is clearly unattainable.

Coupled human and natural systems Coupled human and environmental systems, also called coupled human and natural systems (CHANS) are integrated, complex, and dynamic systems composed of human and natural systems that mutually interact with each other. Treating CHANS individually, one-way, and linearly is no longer a valid assumption [190]. The reciprocal interactions between human-natural systems have long been recognized, but their complex interactions and patterns have not been fully understood [159, 7]. Reciprocal effects and feedback loops, nonlinearity and thresholds, surprises, legacy effects and time lags, resilience, and heterogeneity across multiple spatial, temporal and organizational scales are some of the features of these coupling systems [118, 119]. Gaining insights about CHANS is vital to the quest for both human well-being and global sustainability [6].

Water resource systems belong to CHANS category. They are part of environmental systems and mutually interact with humans. For instance, let's define a new dam project in a transboundary river basin. We know that the new dam has effects on people and ecosystem. For example, the new dam interacts with the atmosphere. The land interacts with the atmosphere with/without a time lag as well. Thus, the new dam indirectly interacts with the land. The project also changes current flow regime and this has an impact on downstream ecosystem, people and fishery habitats. A great amount of electricity can be generated. More people might migrate to the river basin and the economy can improve. Now the question arises is it "good" to construct the new dam? Lack of clear understanding of this system leads to a solution which is not sustainable.

Stationary and non-stationary A stationary process is one whose statistical properties (i.e., mean and variance) do not change over time [49]. Many water resource systems have been managed under stationary assumptions. However, these assumptions for coupled human-water systems are usually not valid [130]. According to Milly et al. in 2008 [136], stationarity should no longer be considered as a main assumption in water resource risk assessment and planning. They also argue that the significant anthropogenic change of Earth's climate leads to varying the means and extremes of important patterns, such as precipitation, evapotranspiration, etc. [136]. Hirsch later explains that in order to include non-stationarity in water resource planning and management analysis one should have a strong scientific basis for this assumption [81]. Milly et al. in 2015 [135] argue that in order to consider representations of the water cycle process (i.e., evaporation, transpiration, condensation, precipitation, and runoff) in water resource systems planning problems one generally needs to assume non-stationarity. For further information about stationarity and non-stationarity the reader is refereed to the sources [161, 104, 140].

Climate change Climate change is a change in the pattern of climate over a long period of time, and may be due to a combination of natural and human induced causes [145]. In the 20th century climate has altered (getting warmer) with a rate that is unprecedented compared with the last hundred years. Based on the fifth assessment report published by the intergovernmental panel on climate change, human activities over the past fifty years are the cause of this warming [147]. According to Cook et al., there is 97% agreement about this fact [40].

There is a relationship between climate change and water resource planning and management. Climate change has altered the water cycle causing rising sea levels, having more rain and less snow, increasing the probability of heavy rain and extreme droughts. Climate change affects different aspects of extreme events, such as frequency, duration, intensity, and timing. Figure 2 (a) shows how a small change in average mean temperature causes a drastic change in the frequency of an extreme event. When the climate is normal the likelihood of an extreme event can be displayed like a traditional bell curve. Figure 2 (b) illustrates the role of moderate weather events. It shows that even a tiny shift in temperature variance leads to flattering the curve and altering frequency of extreme events. Figure 2 (c) depicts the combination of both aforementioned effects. It shows a small change in average mean temperature combined with moderate weather events (flattering the curve) cause the frequency of extreme events drastically change (see the colored area).

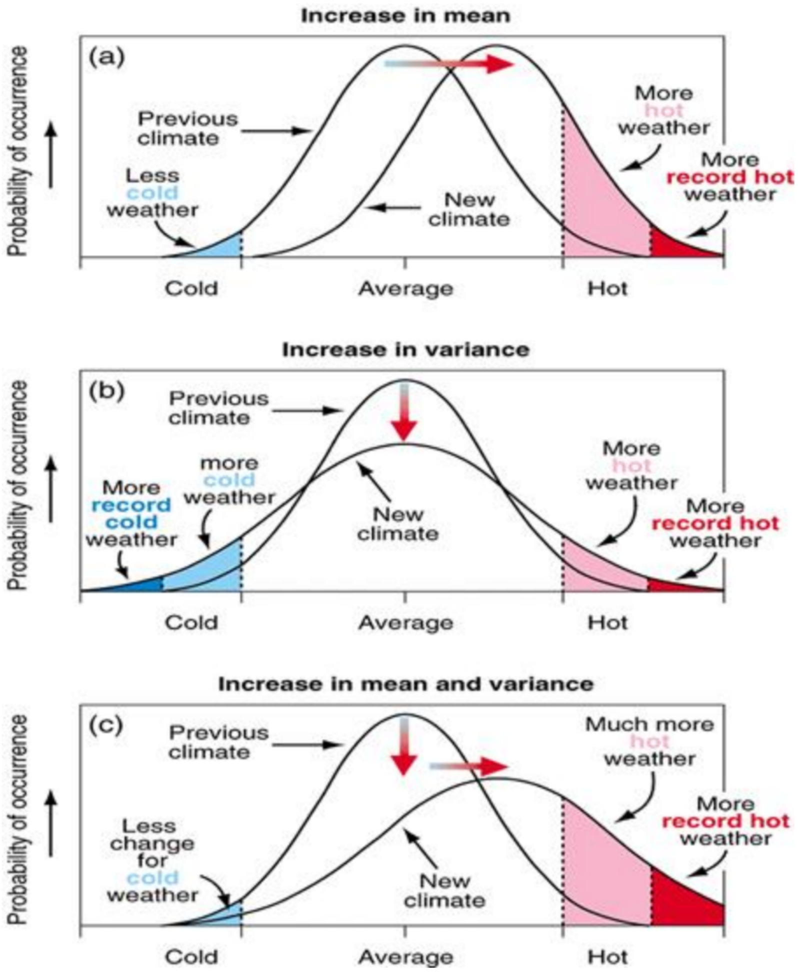

Figure 2: Graph representing how a shift and/or widening of a probability distribution of temperatures affects the probability of extremes (adapted from [131])

Complexity Water resource systems are inherently complex systems. Some of this complexity is rooted in the aforementioned reasons that a decision maker needs to consider while modeling. They are also complex due to their tightening relationships with various social, political, physical, and economic systems and subsystems. These nonlinear systems interact with many other nonlinear systems which makes problems of water resource system planning and management challenging.

Figure 3 depicts the factors that affect the water resource management problem. Additionally, there are interactions amongst different factors. The scale shows the goal of balancing supply and demand. In this thesis, we focus on one of the above factors, namely uncertainty. Dealing with uncertainty from the above list, we will use a well-known methodology from operations research (OR), called robust optimization which we will describe in Section 2.3.2. We also address deep uncertainty using robust decision making which is described in Section 2.3.1. In order to assess the alternatives multiple attribute decision making is applied.

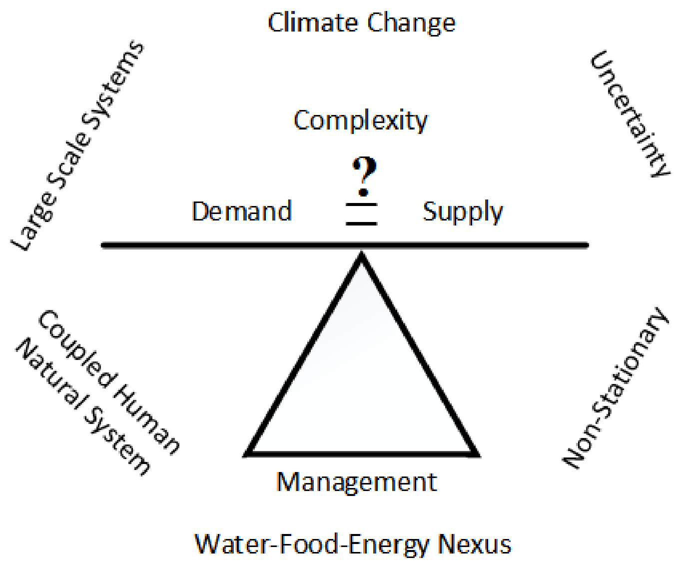

Figure 3: Factors that affect water resource systems management problem

2.1.2 Water resource management problems

Water is one of the vital resources for most human activities and governments invest thousands to millions of dollars on water resource management projects each year. Even then, there are many people who do not have access to a reliable, clean, piped water supply. Managing a water resource system is a significant task, including building a new system, expanding the current system, and operating an existing one.

Water resource management and planning problems are very diverse. They are different in terms of their sizes. They can be small in the size of an area in a city, a connected network amongst cities or provinces, on the scope of a huge basin that crosses a number of provinces, and even as big as a country. They require different kinds of decisions dependent on their phases. For example, decisions in a water distribution system are classified into four different phases: (1) layout (2) design

(3) programming, and (4) planning [44]. Water resource management and planning problems are time dependent. They can be examined at different time resolutions (i.e., weekly, monthly, yearly, etc.) and decisions in one period have effects on the other periods. They are constructed owing to varying goals. For instances, the main goal of planning water supply systems are: (1) optimal network design to decrease the investment costs, and (2) optimal network operation to minimize running costs [31]. They also include reclaimed water management that aims to fight water scarcity and water ecosystems degradation and enhancing economic and social welfare. Another example is flood controlling with the purpose of decreasing the risk of flooding and erosion to people.

Planning/Managing a water system frequently requires mathematical models, and modeling a real system is challenging. Models of water resource systems are categorized into (1) optimization vs simulation, (2) surface water vs ground water, and (3) water quality vs water quantity [85]. D'Ambrosio et al. [42] divides optimization-based water resource system models used in the field of drinking water distribution network into (1) network design and (2) network operation. Optimization-based water resource models can be (1) deterministic, (2) non-deterministic, (3) linear, and (4) non-linear. Based on Kelly et al. [50] five common modeling approaches are: system dynamics, Bayesian network, coupled component models, Agent-based models, and Knowledge-based models [50].

2.1.3 Overview of water resource management approaches

In this section, the most prevalent approaches for water resource management are explained. The approaches are categorized into three groups, namely simulation, optimization, and simulation-optimization methods.

Simulation methods

Simulation models frequently use various alternatives to generate results, then followed by checking for optimality. They address "what if" questions and optimality is not guaranteed. They are widely applied owing to being easy to use and requiring minimum computer time and storage [83] and because they can model very complex systems that cannot be represented by analytical methods.

System dynamics (SD) SD is a systematic tool that uses concepts of systems theory to interpret and simulate the nonlinear behavior of complex systems and analyze how they vary over time. It applies mental models, feedback and causal loop diagrams, stock and flow, material delays, and information delays to enhance learning in complex systems and lead to design better policies. SD applies a top-down modeling approach by modeling a system by breaking it into its major components and interactions [124]. It is also among five common modeling approaches for integrated environmental assessment and management [96]. The origin of SD traces back during the mid-1950s by Professor Jay W. Forrester at MIT [55]. SD has extensively been used to assess candidate policies by running "what if" simulations and as a suitable tool for communicating with stakeholders. SD applications lie in diverse areas, but play an important role in water resources management (see [137, 71, 150, 200, 99, 103, 175, 102, 143, 178, 151]). More details on SD modeling can be found in the references [174, 106, 54]

Agent-based modeling (ABM) ABMs are a class of computational models in which a complex system is considered as a set of autonomous active, proactive, or social agents/actors interacting in a shared environment. ABM techniques are classified as "bottom-up" approaches owing to the fact that the system is modeled via modeling its individual entities and their interactions [124]. In ABM, we know that *phenomena* is made up of its parts, but it is more than the sum of its parts because there are interactions between them. Additionally, *emergent phenomena* is explained by the result of the interactions of individual entities with each other and the environment. It is also worth mentioning that although emergent properties are described by the interaction of parts, just being aware of the properties of the parts does not describe or predict what will emerge. For instance, a traffic jam, which is made up by the interactions between drivers moves into the opposite direction of the cars that cause it. For more information about emergent phenomena, the reader is refereed to the sources [93, 133]. According to Bonabeau [23] the three main advantages of ABMs over other tools are: (1) it captures emergent phenomena; (2) it provides a natural explanation of a system, and (3) it is flexible. Due to these strengths ABM is commonly applied to deal with water resource management problems [138, 19, 97, 57, 64, 63, 45]. For more information about ABM, the reader is refereed to the reviews by Samera et al. [2] and An [8].

Robust decision making (RDM) This is one of the two main methodologies of the thesis. For more information about robust decision making the reader is referred to Section 2.3.1. This methodology is applied to our problem on interest, management of river basins under deep uncertainty, in Chapter 4.

Decision scaling (DS) This is a systematic bottom-up decision analysis method that was developed in 2008 through the Upper Great Lakes International Joint Commission in North America [30, 191]. "DS is a robustness-based approach to water system planning that makes use of a stress test for the identification of system vulnerabilities, and simple, direct techniques for the iterative reduction of system vulnerabilities through targeted design modifications" [153, p. 16]. It also engages stakeholders in the process of developing robust strategies [27]. Water resource managers and decision makers can use DS framework in order to deal with numerous uncertainties affecting water resource planning. DS has been applied in a number of water resource planning applications (for instance, [58, 29, 30, 28, 148, 98, 173, 148]).

Optimization methods

Optimization models address "what should be" questions via minimizing or maximizing an objective function subject to system constraints. Plenty of designers use mathematical programming approaches instead of finding a complex set of rules that account for any combination of supply and demand [87]. Optimization methods are used in water resource systems problems for planning, scheduling, allocating, operating, designing, etc.

Stochastic optimization (SO) This approach refers to a group of methods for minimizing or maximizing an objective function when randomness is present [75]. SO is a mathematical tool that models the uncertain parameters using probability distributions and it is a quite popular in water resource management. Some of these applications are: water allocation [205, 122, 121, 120, 34, 116, 197], reclaimed water distribution network design [203, 204, 202], river basin irrigation system management [142], and reservoir management [59, 180, 60, 41].

Info-gap decision theory (IGDT) This methodology was developed by Yakov Ben-Haim when he studied the reliability of mechanical systems [12]. IGDT is a non-probabilistic decision making framework that seeks to maximize robustness to failure, or opportunity for windfall success in situations of deep (or severe) uncertainty [13, 14, 78]. IGDT addresses two consequences of uncertainty: (1) the threat of failure, and (2) the possibility of unimagined success [14]. Some of the water resource management applications that used IGDT are: water supply system expansion problem [130], water resource planning [154, 101], suitable adaptation strategy selection under climate change and future demand uncertainties [155], water catchment management [132], flood risk management [79], and groundwater remediation [146]. For more information regarding IGDT the reader is referred to the sources [14, 16, 15, 169, 17].

Robust optimization This is one the two main methodologies of the thesis. For more information about robust optimization the reader is referred to Section 2.3.2. This methodology is applied to our problem of interest, management of river basins under uncertainty, in Chapter 5.

Multi-criteria decision analysis/making (MCDA/M) This methodology is a sub-discipline of operations research that seeks to find the best solutions amongst a set of alternatives considering different frequently conflicting criteria. MCDA/M is divided into multiple-attribute decision making (MADM) and multiple-objective decision making (MODM). In water resource systems planning and management problems, decision makers (stakeholders) are interested to evaluate the alternatives and find the best decision. The applications of MCDA/M in water resource planning and management include wastewater treatment technology selection problem [94], regional water restoration management [182], sustainable strategy selection in a river basin [33], and reservoir operation management problem [24]. For further information about using MCDM/A in water resource system management problems the reader is referred to sources [73, 72].

Metaheuristics Metaheuristics are one of the common approaches used for solving water resource management problems. According to Glover and Kochenberger [65] "metaheuristics are solution methods that orchestrate an interaction between local improvement procedures and higher level strategies to create a process capable of escaping from local optima and performing a robust search of a solution space". The reason is that numerous water resource systems encompass non-linear and non-convex functions in their modeling process due to their physical properties (i.e., the relationship between outflows versus elevations in reservoirs, the head loss, or pressure loss, in piping water systems, etc.). Thus applying exact algorithms is arduous even sometimes impossible for large scale problems (see [42, 25]). Some of the applications of using metaheuristics are problems such as optimal operation of multi-reservoir system [3], optimizing the rule curves of a multi-purpose reservoir system [35], and optimizing water distribution network design [10, 61].

Simulation-optimization methods

The combination of simulation-optimization methods is also applied in water resource planning and management problems. For example, Taghian et al. [176] used a hybrid simulation-optimization model to extract the optimum policy for reservoir operation under both normal and drought conditions. Huan and Chiu [84] applied a coupled simulation-optimization for Seawater Intrusion Management. Fang et al. [52] employed a simulation-optimization model to optimize the key points of the water diversion curves, the hedging rule curves, and the target storage curves. For more information the reader is referred to sources [152, 11, 206].

2.2 Problem of interest: water resource planning and management at river basins

River basin water resource planning models are special classes of water resource systems management models that tackle allocating water at basin scale. They are composed of natural channels, reservoirs, rivers, irrigation areas, hydropowers, cities, industrial areas, etc. Simulation, optimization, and simulation-optimization approaches are routinely employed for managing and planning water at river basins. Their common goal is to balance supply and demand via distributing the water based on allocation priorities and follow policies to share the deficit. The priorities are the key factors that affect the allocation results, and they can lead to a decision in which a downstream user might completely bypass an upstream user.

Simulation, described in Section 2.1.3, has been used for managing of water at river basins. For example, Madani and Mario applies SD for managing Iran's Zayandeh-Rud River Basin [125]. Bloom [22] uses RDM to develop a new decision support for the Colorado River Basin problem management. ABM is employed for simulation of water-sharing problem in Tamilnadu, India [139].

Optimization, described in Section 2.1.3, has been used for planning and managing of water at river basins. These kind of models are commonly applied to optimally allocate surface water into different competing demands. [171] applies stochastic dynamic programming to define a reservoir release policy for a dam at Aswan in the Nile River Basin. [38] uses RO to design a water supply system under uncertainty considering correlated model of data uncertainty. [76] develops a model that can represent non-linearities in river basins for solving the optimal water allocation problem. [142] develops two stage scenario-based stochastic programming model for water management in the Indus Basin Irrigation System. Ghasemi [62] uses RO for planning an integrated water system. [41] compares between RO and SO for long-term reservoir management under uncertainty.

Initial studies of river basin planning models are related to reservoir operation management models owing to the critical role of reservoir in water resource systems. Yeh [198] in 1985 reviewed the first theories and applications of system analysis for reservoir operation and divided them into the following categories: linear programming (LP), dynamic programming, non-linear programming, and simulation. In the same year, Wurbs [193] summarizes the application of optimization techniques used for reservoir management by listing over 700 references and concludes that optimization is suitable for this purpose. He extends the work published by Yeh [198] related to the reservoir operation, and presents an annotated bibliography in which applied systems analysis is divided into simulation, optimization, and stochastic methods.

Wurbs in 1991 [192] sorts numerous reservoir system analysis models, compares them focusing on practical applications, and outlines modeling considerations. Wurbs [194] in 1993 groups reservoir system analysis models into: simulation models, optimization models, and system analysis models that used network flow programming formulation. Labadie [107] in 1997 presents a survey of reservoir system optimization models and argues that the goal of many studies is planning instead of conducting operational scheduling. He also asserts that there is a gap between theory and practice owing to the mathematical complexity of the models and users' lack of confidence. A great number of lately papers regarding derived operating rules for single-purpose reservoirs in series or in parallel are reviewed by Lund and Guzman in 1999 [123]. Based on their view the operating rules are capable of being supported for engineering optimization purposes.

In 2004, Labadie [108] updates the previous review concerning multi-reservoir systems optimal operation. In this extensive review many optimization methods, such as LP, network flow optimization, non-linear models, stochastic optimization , and multi-objective optimization are examined; and future directions for further researches and applications are suggested. Rani and Moreira [152] in 2010 surveys simulation, optimization, and simulation-optimization approaches applied for reservoir systems operation problems at basin scale and outlines the reported applications. Fayaed et al. in 2013 [53] argues that reservoir operation is a challenging task for water resource managers and planners. He also analyzes the prior studies critically and concludes that optimization methods combined with simulations have shown the most reliable results. Then he suggested to integrate proposed stochastic dynamic programming and artificial neural network for this purpose. In 2014, Ahmad et al. [5] studies the contemporary optimization methods utilized in reservoir operation. The discussed topics includes evolutionary algorithms, combination of simulation-optimization, and multiple objective optimization methods. [188] reviews the state-of-the art researches on operation of multi-reservoir system and states that the basic main classification of optimization techniques consisted of (1) LP, (2) dynamic programming, and (3) non-linear programming; either in deterministic or stochastic environment.

2.2.1 Linear models in planning and management of river basins

Computer models also play an important role in planning and management of river basins. Using computers dates back to 1960s, and optimization-based models have been the mainstay of many computer models. The river system commonly is regarded as a network flow problem with LP formulation. LP is popular due to the fact that LP formulation can represent water licensing systems or priority of supply, which is still in use in North America (NA) where many original models has developed [87]. "First in time, first in right" principle is the first founded basis for water users appropriation doctrine that widely applied in western United States. Water-seniority and use priority are established many years ago and dictates that in dry periods users are shorted according to their seniority.

A river basin system is mainly formulated as a network with arcs and nodes in which all flows through the arcs are weighted by costs and the objective function is minimization of the overall flow in the whole network. More precisely, the priority is set to several users and water distribution is made based on the importance of users. The objective is to maximize supplies to all users considering their respective priorities. There are weights for all the flows in the network based on unit cost which alters in each arc. Costs are convex economic losses and the optimization is conducted via minimizing the summation of flow costs.

Early efforts are concentrated on to implement efficient solvers that works in (NFAs) network flow algorithms-based models. Out-of-Kilter [56] algorithm usually is utilized as the main algorithm in many software. The procedure starts with guessing the upper and the lower bounds. Next, the minimization problem is solved and the obtained flow solutions are checked with the assumed bounds. According to the new solution, the bounds are reset to new values and the steps are reiterated if necessary until the assumed bounds and the network flow solution are within a reasonable tolerance limit [86, 87]. However, there is no guarantee that applying this algorithm leads to a convergence to the global optimum [88]. In what follows, the main computer models used for water resource systems planning and management at the basin level are provided.

2.2.2 River basin modeling software

The Texas Water Development Board (TWDB) starts developing a series of surface water-simulation models in the late 1960s. SIMYLD is developed by Evenson and Moseley in 1970 for managing a multibasin and interconnected water resource in Texas. Then, it is turned into SIMYLD-II which is the result of substantial modification of its former versions [46, 51].

In 1970, Sigvaldson [166] develops a ground-breaking method using network flow programming for managing reservoir systems operations, which later evolves as arc reservoir simulation program. The study is conducted by Acres Consulting Services and the case study is conducted in the Trent River Basin in Ontario, Canada.

Two other models that are developed by TWDB to simulate and optimize an operation of a water system are: The Surface Water Resources Allocation Model (AL-V) for long-term planning [129] and Multireservoir Simulation and Optimization Model (SIM-V) for short-term planning [126]. Their modeling capabilities include to model an interconnected system of reservoirs, hydroelectric power plants, pump canals, pipelines, and river reaches [127]. The California Department of Water Resources is developed a water resources planning model (DWRSIM) to simulate the operation of two combined projects [37]. The projects called the California State Water Project (SWP) and the Federal Central Valley Project (CVP).

[26] discusses Central Resource Allocation Model (CRAM) a water resource model that used to prepare a raw water supply Master Plan for the city of Boulder, Colorado. The Kern conveyance operations model (KCOM) is designed by [9] to plan the Kern Water Bank, in Kern County. Another software which is developed by the same company is MONITOR-I [128]. The aim of this software is to investigate complex surface water storage and conveyance systems operated for hydroelectric power, water supply, and low flow augmentation. Water Assignment Simulation Package (WASP) is developed by [105] to analyze the water system of Melbourne, Australia.

MODified version of the SIMYLD model (MODSIM) is a software which the initial developed version dates back to the 1970's at Colorado State University [110]. A decision-support tool for the water supply network of City Fort Collins is designed by Labadie et al. [110, 109]. The aim of their model is to find the best way to allocate water considering flow rights, storage rights, and different ways of substituting water from several sources.

An economic-engineering water model named California value integrated network (CALVIN) is developed to allocate water in California's inter-tied complex system. The software is a work at the University of California at Davis under the sponsorship of several agencies [91]. The model's development, calibration, limitations, and results are discussed by Draper in 2003 [48]. Jenkins in 2004 [92] illustrates the value of optimization modeling for a complex multipurpose water system, including fifty-one surface reservoirs, twenty-eight groundwater basins, nineteen urban economic demand areas, twenty-four agricultural economic demand areas, thirty-nine environmental flow locations, one-hundred thirteen surface and groundwater inflows.

Water Resources Management Model (WRMM) developed for Alberta Environment (a water management agency in the province of Alberta, Canada) utilizes optimization algorithms to aid opting the best allocation policy [86, 89]. A generalized regional water allocation simulation model (GWASIM) is a model that capable of incorporating the impact of flood-induced reservoir turbidity into water supply [36].

Most of the above-mentioned computer models are still in use, and some early versions have evolved to more sophisticated models. Amongst all reviewed computer software, NFP is the common approach for managing complex multiple-reservoir water storage and distribution systems. Additionally, in most of these models Out-of-Kilter algorithm is still the main algorithm. However, one drawback of using this algorithm is that there is no guarantee that applying this algorithm leads to a convergence to the global optimum [88].

Although there are lots of studies with regard to river basin planning and management, to the best of our knowledge there is not a study that uses RO with directed multi-graph without loops for modeling such a system. Ergo, one of the aims of this thesis is to provide a procedure with a concrete mathematical formulation for planning water allocation system in a river basin using RO. Additionally, in the case of deep uncertainty and lack of agreement among decision makers about the uncertainty sets, we employ RDM for water resource systems planning. The combination of RDM and MDAM for water resource systems planning is also another research direction that we take in this thesis.

2.3 Methodologies of choice

In this section, we elaborate on the two main methodologies of the thesis, robust decision making and cardinality constrained robust optimization. Robust decision making is used in the case of deep uncertainty and lack of agreement among decision makers about the uncertainty sets, while RO is used when there is agreement among decision makers about the uncertainty sets.

2.3.1 Robust decision making

This is a methodology that uses simulation models to aid decision maker(s) to design robust strategies whose components might not be obvious at onset. Based on Lempert et al. [114] "a robust strategy performs relatively well compared to alternatives across a wide range of plausible futures". More precisely, there is lack of agreement amongst decision makers about the uncertainty sets. RDM provides a prescriptive, systematic, and quantitative approach for choosing candidate strategies [114]. It is an iterative decision analytic framework that characterizes vulnerabilities of such strategies, and assesses the trade-offs amongst them (see Figure 4). The steps are as follows:

1. Define performance goals
2. Identify a candidate strategy
3. Generate future scenarios using the available mathematical models
4. Assess the system performance and determine the future scenarios that make the system vulnerable
5. Create new strategies based on the information obtained from step 4
6. Repeat steps 3 to 5 for all other candidate strategies
7. Do trade-off analysis and select the robust strategy

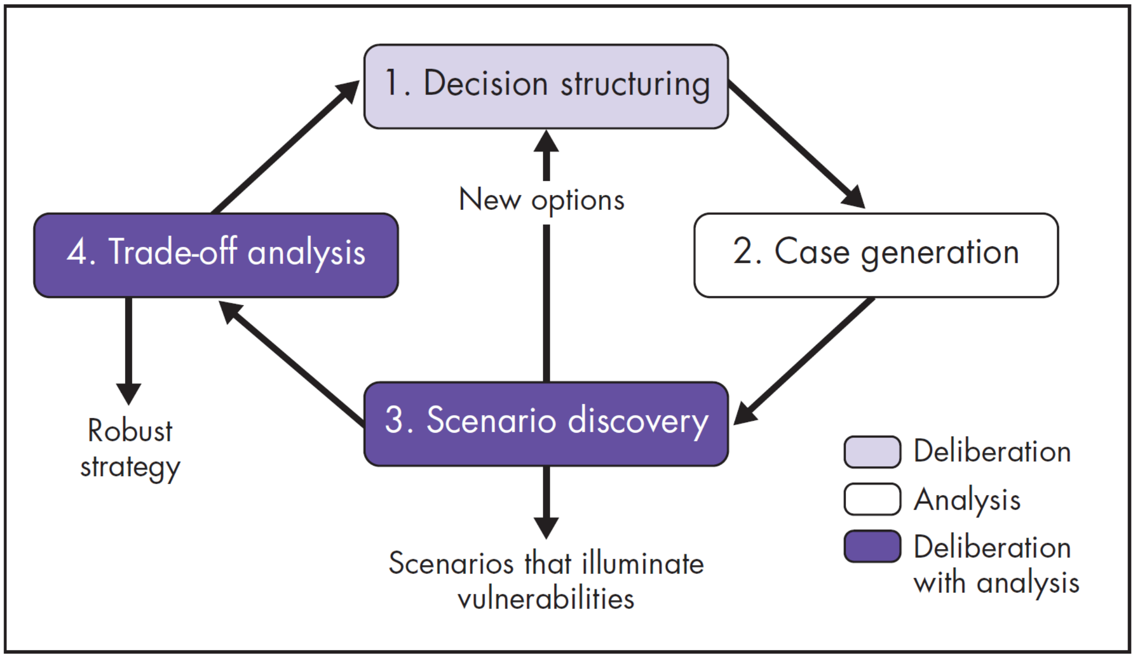

Figure 4: Iterative, participatory steps of an RDM analysis (adapted from [115])

RDM was developed by Lempert, Popper, and Bankes at RAND [111] for situations that include deep uncertainty, and it has been presented in many applications, including water resources planning [68, 112, 164, 177, 165], energy policy [149], climate change adaptation [43], the U.S. terrorism insurance risk act [47], and coastal resilience areas. It is different with a traditional predict-then-act analysis (top-down approach) that seeks to find optimum solution which is highly dependent on predictions. Instead, it searches for finding a robust solution that performs satisfactory (bottom-up approach) under a wide range of plausible futures. The reader is refereed to the papers for further information [189, 74, 187, 163, 69, 113, 43].

2.3.2 Cardinality constrained robust optimization

In this section, we elaborate on robust optimization. RO is a sub-discipline of OR that searches to find an optimum solution with a certain measure of robustness against uncertainty. Uncertainty is represented deterministically in terms of variability of the values of the problem parameters. Robust solution is feasible for any realization of the uncertainty in a given set. Thus, this solution is called robust as it can tolerate certain amount of parameters' variations while remaining feasible.

In this thesis, we use cardinality constrained robust optimization to formulate a water resource system planning under demand uncertainty. The planning problem aims to optimally allocate water at river basins. We choose this methodology after reviewing classical robust optimization approaches in the literature. The three common applied methods were developed by Soyster [170], Ben-Tal and Nemirovski [18], and Bertsimas and Sim [20]. The first approach is too conservative and might lead to give up too much of optimality. The second one leads to quadratic and conical robust optimization problems. The third approach, which is the one that we select, has the better performance considering solution quality and computational efficiency [62]. This approach also allows the decision-makers to adjust the level of conservatism of the model.

The cardinality constrained robust optimization method is proposed by Bertsimas and Sim [20] for both linear discrete and continuous optimization problems. In what follows, we present here the main ideas, steps, and an overview of the method. For more details, the reader is referred to Bertsimas and Sim [20]. Let's consider the following *nominal* linear programming model:

$$\begin{aligned} \text{Maximize} \quad & \mathbf{c}'\mathbf{x} \\ \text{s.t.} \quad & \mathbf{A}\mathbf{x} \leq \mathbf{b} \\ & \mathbf{l} \leq \mathbf{x} \leq \mathbf{u}. \end{aligned} \tag{1}$$

We assume that in the above programming model, data uncertainty only affects the elements of matrix $\mathbf{A}$. Consider the ith constraint of this optimization problem $\mathbf{a_i'x} \leq b_i$. Let J_i be the set of coefficients in row i, which is represented by $a_{ij}, j \in J_i$, that are subject to parameter uncertainty. Each element of matrix $\mathbf{A}$ is modeled as a symmetric and bounded random variable where $\tilde{a}_{ij}, j \in J_i$ takes values from the ranges $[\bar{a}_{ij} - \hat{a}_{ij},\ \bar{a}_{ij} + \hat{a}_{ij}]$. The mean value of the $\tilde{a}_{ij}, j \in J_i$ is represented by $\bar{a}_{ij}$ and it is equal to the nominal value of $\tilde{a}_{ij}$. We define a new random variable (also called scaled deviation) $\eta_{ij} = (\tilde{a}_{ij} - \bar{a}_{ij})/\hat{a}_{ij}$, associated with each uncertain entry that follows an unknown but symmetric distribution, and takes values in the interval $[-1, 1]$. As the scaled deviation takes values from the interval $[-1, 1]$ for each row (constraint) i with j decision variables, the summation of all scaled deviations can take any value between $-n$ and n. It is worth mentioning that some parameters will surpass their nominal values while others will take values below their nominal values.

For every constraint that has at least one uncertain parameter a new parameter called the *budget of uncertainty* and denoted by Γ is introduced. We define Γ_i for constraint i that takes values, not necessarily integer, from the range $[0, |J_i|]$. The role of the parameter Γ_i is to control the trade-off between the robustness of the suggested method and the level of conservatism of the solution. The violation of constraint i is protected applying this method, when only an already identified number Γ_i of the coefficients varies. Consequently, having less than or equal to Γ_i uncertain coefficients, the approach guarantees that the solution is feasible. This method shields decision makers from all cases up to number $\lfloor \Gamma_i \rfloor$ of coefficients changes, plus one coefficient $a_{it}, j \in J_i$ varies by $(\Gamma_i - \lfloor \Gamma_i \rfloor)\hat{a}_{it}$. The key property of the method is that if the nature acts in such a way that all $a_{ij}, j \in J_i$ alters, then the robust solution is deterministically feasible, and additionally, the solution might remain feasible, even if more than $\lfloor \Gamma_i \rfloor$ varies.

We define a non-linear formulation for the above-mentioned situation:

$$
\begin{aligned}
\text{Maximize} \quad & \mathbf{c}'\mathbf{x} \\
\text{s.t.} \quad & \sum_j a_{ij} x_j \\
& + \max_{\{S_i \cup \{t_i\} | S_i \subseteq J_i, |S_i| = \lfloor \Gamma_i \rfloor, t_i \in J_i \setminus S_i\}} \Big\{ \sum_{j \in S_i} \hat{a}_{ij} y_j + (\Gamma_i - \lfloor \Gamma_i \rfloor) \hat{a}_{it_i} y_t \Big\} \\
& \leq b_i \qquad\qquad \forall i \\
& - y_j \leq x_j \leq y_j \qquad \forall j \\
& \mathbf{l} \leq \mathbf{x} \leq \mathbf{u} \\
& \mathbf{y} \geq \mathbf{0}.
\end{aligned} \tag{2}
$$

In the above mathematical programming model, if one considers Γ_i as an integer, the ith constraint will be protected by $\beta_i(\mathbf{x}, \Gamma_i) = \max_{\{S_i | S_i \subseteq J_i, |S_i| = \Gamma_i,\}} \big\{ \sum_{j \in S_i} \hat{a}_{ij} |x_j| \big\}$. It is worth mentioning that when $\Gamma_i = 0, \beta_i(\mathbf{x}, \Gamma_i) = 0$, the model is equal to the nominal problem. If one deems $\Gamma_i = |J_i|$, the model is equal to Soyster's model [170].

To reformulate model (2) as an LP, we use the following proposition [20]:

Proposition 1. Given a vector $\mathbf{x}^*$, the proposition function of the ith constraint,

$$\beta_i(\mathbf{x}^*, \Gamma_i) = \max_{\{S_i \cup \{t_i\} | S_i \subseteq J_i, |S_i| = \lfloor \Gamma_i \rfloor, t_i \in J_i \setminus S_i\}} \Big\{ \sum_{j \in S_i} \hat{a}_{ij} |x_j^*| + (\Gamma_i - \lfloor \Gamma_i \rfloor) \hat{a}_{it_i} |x_j^*| \Big\} \tag{3}$$

equals the objective function of the following linear optimization problem:

$$\begin{aligned} \beta_i(\mathbf{x}^*, \Gamma_i) = \text{maximize} \quad & \sum_{j \in J_i} \hat{a}_{ij} |x_j^*| z_{ij} \\ \text{s.t.} \quad & \sum_{j \in J_i} z_{ij} \le \Gamma_i \\ & 0 \le z_{ij} \le 1 \qquad \forall j \in J_i. \end{aligned} \tag{4}$$

Please see [20] for a proof. In order to avoid the non-linearity of adding (4) in the original problem (2), the next step, following [20] is to create the dual of problem (4) as follows:

$$\begin{aligned} \text{Minimize} \quad & \sum_{j \in J_i} p_{ij} + \Gamma_i z_i \\ \text{s.t.} \quad & z_i + p_{ij} \ge \hat{a}_{ij} |x_j^*| \qquad \forall i, j \in J_i \\ & p_{ij} \ge 0 \qquad \forall j \in J_i \\ & z_i \ge 0 \qquad \forall i. \end{aligned} \tag{5}$$

Using strong duality, because problem (2) is feasible and bounded for all $\Gamma_i \in [0, |J_i|]$, then the dual problem (5) is also feasible and bounded and their objective values coincide at optimality. Applying Proposition 1, one has that $\beta_i(\mathbf{x}^*, \Gamma_i)$ is equal to the objective function value of problem (5). Replacing to problem (2), one obtains problem (6) which is an equivalent LP model for problem (2). The LP formulation is represented as follows:

$$
\begin{aligned}
\text{Maximize} \quad & \mathbf{c}'\mathbf{x} \\
\text{s.t.} \quad & \sum_j a_{ij}x_j + z_i\Gamma_i + \sum_{j \in J_i} p_{ij} \le b_i && \forall i \\
& z_i + p_{ij} \ge \hat{a}_{ij} y_j && \forall i, j \in J_i \\
& -y_j \le x_j \le y_j && \forall j \\
& l_j \le x_j \le u_j && \forall j \\
& p_{ij} \ge 0 && \forall i, j \in J_i \\
& y_j \ge 0 && \forall j \\
& z_i \ge 0 && \forall i. \qquad (6)
\end{aligned}
$$

2.4 Summary

In this chapter, we provide an extensive literature review of water resource systems, water resource characteristics, water resource problems, water resource management approaches, river basin water resource management and planning, common computer software for planning problems, RDM, and cardinality constrained robust optimization methodology. Based on this extensive review, we can provide a summary as follows:

(1) Water resource system planning and management is challenging and the modelers should incorporate uncertainty in their models.

(2) Optimization approaches, especially minimum cost network flow problem, constitute one of the common ways for modeling river basin water resource planning problems.

(3) RO is one of the methodologies that can deal with uncertainty in optimization problems in water resource management. RDM is another approach that is common when dealing with deep uncertainty. MADM is also a methodology that can be used for finding the best solutions amongst a set of alternatives considering different frequently conflicting criteria.

Chapter 3

Deterministic water resource planning model

In this chapter, we first describe a deterministic mathematical model for the river basin management problem. Second, we demonstrate the applicability and value of the deterministic model through a set of experiments. This chapter shows the importance and value of using an optimization model for managing river basin systems. In particular, we demonstrate the use of our model, which creates a piecewise linearized function of costs/priorities of the water system, in order to optimally allocate water when there are competing demands and different operating priorities.

3.1 Deterministic water resource planning for river basins

In this section, the process of modeling a river basin planning problem is discussed. The main concepts, such as components, policies, penalties, storage zones, etc. are explained.

3.1.1 River basin components

River basin is a part of a land that is drained by a river and its tributaries. In brief, we describe the most important components of river basins.

Reservoirs

Reservoirs are artificial or natural lakes that are used to store water during times of excess water and to release water during times of low flow. Sometimes we use them for boating, fishing, and other forms of recreation. Some generate electricity while others store water to be used for irrigation.

Hydropower plants

Almost all river basins have hydropower plants. Hydropower plants are built to produce hydroelectricity. A great amount of water needs to be allocated to them due to their role in generating electricity.

Natural channels

Channels that are made naturally called natural channels. They are usually responsible to carry water between components. As some of them are home to fish, amphibians, etc., they are sensitive to water level alterations.

Water demands

Water demands in river basins can be categorized into municipal, industrial, agricultural, and environmental demands. Depending on a river basin, water demands might have different values.

Inflows

Most common inflows in river basins are rivers. They are in the form of surface water that flows in the river basin. The sources of this water can be rain runoff, snowmelt, etc.

Return flows

Sometimes some portion of a water demand needs to re-enter into the system. In this situation, return flows are used. For example, some portion of water from an irrigation demand returns to the system. In this case, return flows are used.

Apportionment channels

In some river basins, there is an agreement between/amongst two/more regions about water usage and sharing to reduce controversy. For example, they define minimum water requirements for certain channels that carry water. These channels are called apportionment channels.

3.1.2 Operating policies

The term "operating policy" represents the regulation or procedure (rights) for administrating a real system by decision makers. The identified operating policies for managing the physical water resource system need to be incorporated into the model. If there is enough water in the system to satisfy all target demands, the conditions are referred to as *ideal*. Whenever there is not sufficient (or too much) water available, the allocation process is based on a set of specified rules, referred to as *operating policies*. Hence, a desired operational state for each component should be specified by an *ideal level* or *zone*. *Auxiliary* zones can be defined to show situations below and/or above the desired operational state.

The process of incorporating operating policies into the model is dependent on the chosen component (i.e., reservoirs, natural channels, inflows, irrigation, hydropower, apportionment channel, withdraws, etc.). To represent an operating policy, the modeler should define penalties for zones. The penalties can be seen as a unit cost of deviation from the desired condition, or cost of violating the policy. In addition, the use of zones enhances the flexibility of the process owing to the fact that one can consider more than one operating policy for a component.

Figure 5 shows an example of identified operating polices applying the zoning-penalties concept. As can be seen in Figure 5, required water for each component is divided into zones with an associated penalty value. The higher the penalty is, the more severe the consequence of the violation is. In Figure 5, the inside numbers show penalty values. The vertical axis depicts demand satisfaction level (%) compared to the ideal target. Each component of the system should have at least one zone identified by the user(s). Additionally, there is a penalty assigned to each zone that represents its relative priority. For instance, if the water resource manager does not allocate any water to the first zone of the reservoir, the associated penalty with this action is equal to ninety times the amount of violation. The general principle is to distribute water to the zones with the highest priority first, then allocate to the second highest rank, and keep going till there is not any water left. The bounds can have physical representations (i.e., the maximum capacity of a reservoir or a channel) while some show operational limitations (more than 40% water shortage for irrigation area can destroy the whole crops).

To illustrate the process of allocation by using penalty zones, suppose the decision maker wants to use the policy provided in Figure 5 for managing water in the system. The reservoir is the only source of water in this water system and it can store or release water. Assume the reservoir is full, other components are empty, and there is a condition of drought. This means that the system will not receive water from outside and there is a shortage of water. Therefore, the natural channel receives water from the reservoir (as it has the highest penalty, 80) in order to reach the minimum level to avoid this penalty, i.e., a min flow that is 30% of the ideal. Municipal demand has the the second highest penalty (70) after meeting natural channel minimum flow. This demand gets water from the reservoir till 80% of its demand satisfies. Irrigation demand has the third highest penalty (60). So the reservoir distributes its water to this demand and 40% of the demand will be satisfied. The fourth highest penalty belongs to the hydropower. The reservoir sends water to the hydropower till it reaches its 50% of its ideal target. The reservoir loses its water owing to allocating water to the aforementioned components. In the example, the reservoir's water level reduces to its second penalty zone with the penalty value of 40. The reservoir keeps the water due to the fact that it has the highest penalty with respect to the other demands' penalties in this situation. Note that the 60% of reservoir capacity is maintained although the other demands are still not fully satisfied.

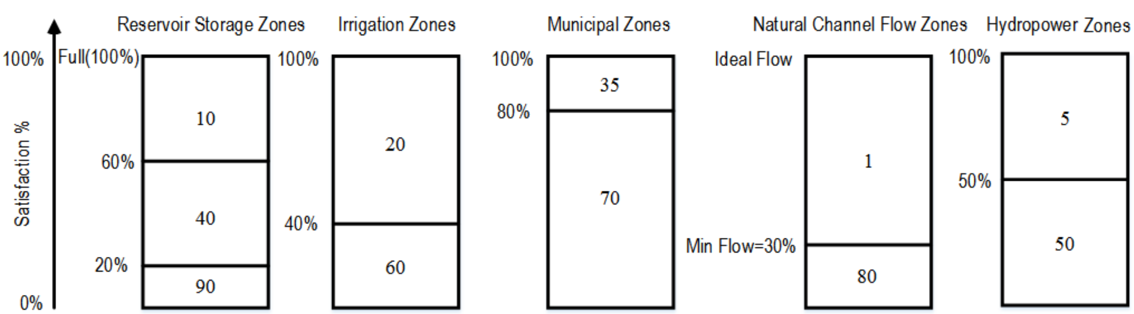

Figure 5: An example of operating policies for different components

After describing the allocation process using operating policies, there is a requirement to mathematically model this process. Thus, in what follows, we will describe how to model operating policies of different components in a network flow model, which will require the definition of multiple arcs.

Reservoir operating policies (rule curves)

Reservoirs are one of the important components of any water resource system, especially river basins. They are responsible to keep water in order to be used for different purposes (irrigation, generating electricity, flood control, recreational activities, fishing, navigation, etc.). A reservoir has a desired operational state which is invariably time-dependent.

The terms "rule curve" or "guide curve" are frequently applied to show the ideal or target storage levels for a reservoir [196]. This is a way to denote operating rules and provide a mechanism for releasing or storing water. Based on this procedure release is a function of storage and every reservoir is subdivided into time-based rule curves. Rule curves (reservoir zones) might be defined as water surface elevation or storage volume versus time of the year [195]. Rule curves can be divided into: (1) ideal storage levels (2) deviations from the rule curve (storages below or above the rule curve). Figure 6 illustrates operating time-dependent rule curves for a reservoir with two zones above the ideal rule curve and four relaxation zones under the ideal rule curve. The line which is named *rule curve* is the ideal target level for the storage. As can be seen in Figure 6, the ideal value is dependent on the month of the year. If the water level is above or below of the ideal rule curve, there is a cost/penalty associated with each unit of flow violation.

In a network flow representation of the system, each rule curve should be modeled by an arc associated with it. This way of modeling was firstly introduced by [166]. It was a ground-breaking method using network flow programming for managing a reservoir operation which later evolved as arc reservoir simulation program (ARSP). One paramount advantage of ARSP is its flexibility in identifying the operational policies (via using rule curves) by users. In addition, it can handle linear programming formulations for individual time intervals [176]. In the modeling process, a reservoir component with its rule curves (reservoir zones) is illustrated by arcs between the reservoir node (RN) and the most downstream node called supply balance node (SBN)

(For an example, see Figure 7, which is the arc representation of the example in Figure 6.). The two zones above the ideal target value rule curve have upper bounds equal to the "flow equivalenced" storage (meaning the volume of stored water divided by the simulation time step) in its respective zone and a lower bound of zero. The rule curve arc has the upper bound and the lower bound equal to the equivalent flow of the ideal target value. The direction of these three arcs are from reservoir node to the SBN. The four relaxation zones are represented by four arcs from the SBN to the reservoir node. The reservoir storage arc is added to keep the remaining storage of the reservoir from the former period at the beginning of the current period. Reservoir storage arcs are used for the following purposes: (1) to satisfy continuity for reservoir nodes when reservoir releases are not equal to inflows, (2) to keep track of changes in storage, and (3) to permit allocation between the reservoir storage and other components. The total amount of flow from the reservoir is equal to the summation of the all arcs considering their directions.

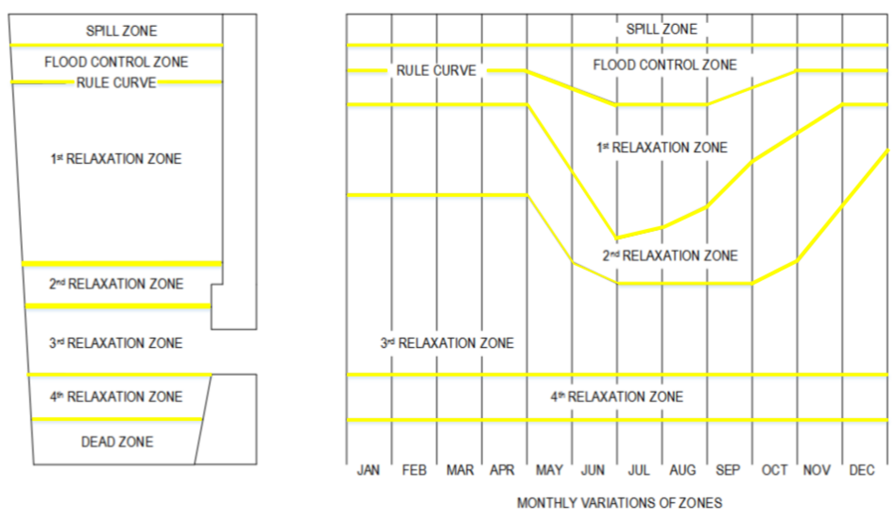

Figure 6: An example of time-based rule curves for a reservoir

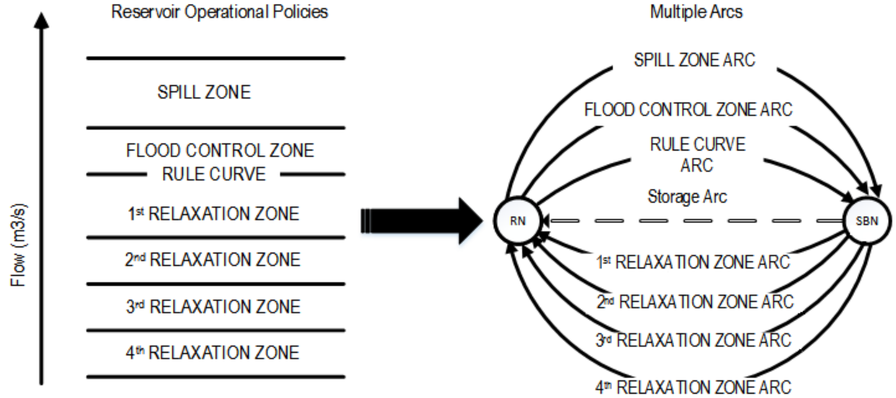

Figure 7: Arc representation of time-based rule curves for a reservoir

Natural channel operating policies

Figure 8 shows operational policies for a natural channel. Figure 9 illustrates transformation process of operational polices into arcs and nodes. The total flow that goes through the natural channel in each period is equal to the summation of all the natural channel arcs, taking into consideration the direction of flow in the arcs. To summarize, there is always flow in the ideal arc; if the other arc is forward arc the flow will be added, and if it is reverse arc the flow will be subtracted from it. Therefore, it is then given by: $F_{\text{Natural Channel}}=F_{UZ}+F_{IZ}-F_{LZ1}-F_{LZ2}$ where if F_{UZ} is not zero, then F_{LZ1} and F_{LZ2} are zero where F_{UZ} is the flow for the upper zone, F_{IZ} is the flow for the ideal zone, F_{LZ1} is the flow for the first lower zone, and F_{LZ2} is the flow for the second lower zone. If flow in F_{LZ1} or F_{LZ2} is not zero, then F_{UZ} is zero. For instance, if the channel flow is in zone F_{LZ2}, then: F_{IZ} will be at its lower bound; F_{LZ1} will be at its upper bound; F_{LZ2} will be between its bounds and F_{UZ} will be zero. More precisely, in order to go to the second lower zone (F_{LZ2}), the first lower zone value (F_{LZ1}) should be in its upper bound. Natural channel zones can have penalties similar to other components. Ideal zone will have the lowest penalty while other zones have more.

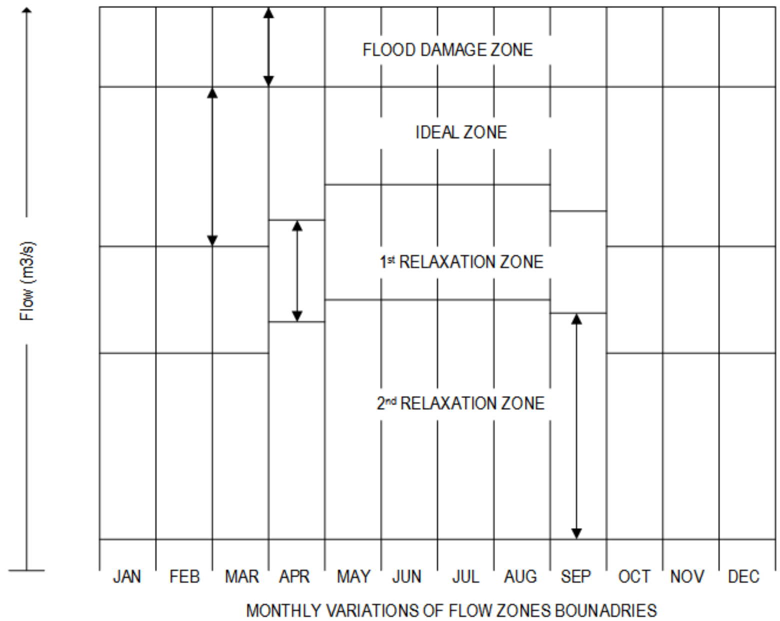

Figure 8: An example of natural channel flow zones

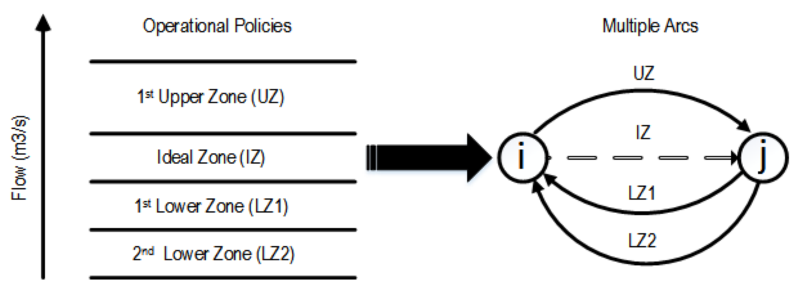

Figure 9: Arc representation of natural channel flow zones

Inflow operating policies

Inflows to the system are modeled by adding an artificial originating supply node which is called the system supply node (SSN) in the network. All inflows to the system are served by this node. Every inflow requires two arcs. One forward arc from the SSN to where the inflow occurs for positive inflows and one reverse arc for negative inflows from where the inflow occurs to the SSN. For both arcs the upper bounds and the lower bounds are equal to the inflow (outflow). When there are no negative inflows, the outflow arc is not required.

Demand operating policies

Demands are represented by a sole arc directed from the node where there is a demand to the SBN. There are target values for demands. The deviation (shortage) from that target value will be penalized.

3.2 Generalized network flow model for managing water resource system at river basins

$G(N, A)$ is a directed multi-graph without loops with a set N of nodes and a set A of arcs connecting the nodes. An arc a in the set A is an ordered pair (i, j) and i and j are nodes in the set N. H_n is a set of arcs whose heads are node n (terminating set of arcs for node n). Terminating set of arcs for node n is also the reverse star (RS) of n. T_n is a set of arcs whose tails are node n (originating set of arcs for node n). Originating set of arcs for node n (tails are n) is also called the forward star (FS) of n. For instance, a set of tail arcs for node i (also called $RS(i)$) shown in Figure 9 is: $\{UZ, IZ\}$. Additionally, a set of head arcs for node i (also called $FS(i)$) depicted in Figure 9 is: $\{LZ1, LZ2\}$.

SSN and SBN are two nodes added into the network to ensure the circulatory property of the system (Please see Figure 12, below, for an example.). Arcs of reservoirs and demands should be connected to the SBN. All inflows need to be connected to the SSN. Nodes are divided into storage-nodes (reservoirs) and non-storage-nodes (other components of the system). N_1 is a set of storage nodes and N_2 is a set of non-storage nodes. $N_1 \bigcup N_2 = N$. $\mathcal{T}$ is a set of time periods $\mathcal{T} = \{1, 2, ..., P\}$.

A reservoir has a number of operating policies and there is an associated elevation level for each operating policy. Each operating policy is represented by an arc and a set of all operating policies for reservoir n is denoted by O_n ($O_n \subset A$). All arcs representing reservoir's operating policies should be connected to SBN. Every reservoir has one and only one extra arc for its storage. B_n represents a set of storage arc for the reservoir n ($n \in N_1$). $B_n \bigcap O_n = \emptyset$ but $B_n \subset A$. Thus in general there are two types of arcs for each reservoir: (1) arcs for reservoir's operating policies (2) a storage arc. The reservoir storage at the end of each time period (e.g. t) can be kept to be used for the next consecutive period (e.g. $t + 1$) and the whole network is connected to the next period by reservoir carry over arcs. Figure 10 shows storage arcs (carry over arcs) example in multi-time-period network configuration. At the end of each period, the summation of flows in the reservoir arcs (except the storage arc) shows the amount of stored water which is kept to be used at the beginning of the successive period in the same reservoir (see constraint (10)). It should be pointed out that while summing, one needs to consider the direction of an arc. The initial storages of all reservoirs at the beginning of the first period are known (see constraint (11)).

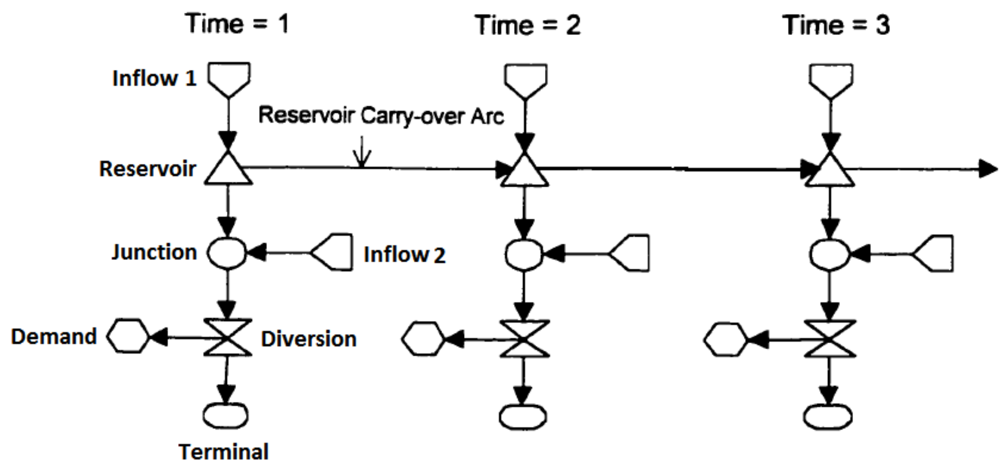

Figure 10: Multi-time-period network configuration (adapted from [179])

3.2.1 Modeling

Priorities Water licensing or priority of demand represents allocation policies at many river basins. Priorities are a systematic way of distributing water in a water system. One way to model priorities is to define cost/penalty per unit of flow deficit, where deficit is the difference between the target demand (ideal value) and the actual demand. The more the deviation, the more cost needs to be paid. The costs can be calculated based on estimates obtained from evaluating the effect of shortage and the money that is needed for compensation. For instance, if an irrigation area in the network receives less than a certain amount of water the crops will be destroyed and the government should pay for it.

Reservoirs To model a reservoir properly, one should consider its physical properties. As a result, the upper bound for storage arc has a physical representation (the maximum capacity of a reservoir) while its lower bound shows the operational limitation (a minimum amount of water that a reservoir should have to function).

Precipitation, evaporation, water loss, and leakage in water systems In order to model a water system more accurately, one should ponder possibility of any loss or gain in the system. For instance, some part of the water from a reservoir might be evaporated. Another example could be rain that increase its water level. A natural channel may lose some of its water during transition. These mentioned conditions are related to weather conditions (i.e., temperature) or physical properties of an element (i.e., a natural channel). In order to model these states, a gain/loss coefficient g is identified in the model that shows the net gain or loss.

Capacity of arcs The upper bound and lower bound of arcs can have physical meanings. For reservoirs, the lower bound is the minimum operating amount of water that must be in the reservoir to function.

Notation

Sets and parameters

- N is a set of nodes which is indexed by n.
- A is a set of directed arcs which is indexed by a.
- H_n is a set of arcs whose head is node n.
- T_n is a set of arcs whose tail is node n.
- N_1 is a set of storage-nodes.
- N_2 is a set of non-storage-nodes.
- $\mathcal{T}$ is a set of time periods which is indexed by t.
- O_n is a set of rule curve arcs for reservoir n.

- B_n is a set of storage arc for storage node n. In order to keep track of the storage, the storage arc (carry-over arc) is defined for each reservoir in each period.

- D_n is a set of demand arcs for node n.

- I_n is a set of inflow arcs for node n.

Parameters

- l_a^t is the lower bound of the arc a in period t.

- u_a^t is the upper bound of the arc a in period t.

- c_a^t is the penalty/cost for one unit of flow of deficit (deficit is the deviation from the target demand) in period t for arc a.

- g_a^t is the gain/loss coefficient for the arc a in period t. The gain is associated with the precipitation and the loss is associated with evaporation or leaking. It is important to note that in time t and for arc a there is either a gain or a loss coefficient not both.

- INF_n^t is the amount of inflow to the node n at period t.

- DEM_n^t is the amount of demand at node n in period t.

- INS_n^1 is the initial storage of storage-node n which is a reservoir at the beginning of the first period $t = 1$.

Decision variables

- x_a^t is the amount of flow passing through arc a from its tail (or from-node) to its head (or to-node).

- r^t is the loss/gain amount of flow from the system in period t.

The problem can be formulated as follows:

$$\text{Minimize} \quad \sum_{t\in\mathcal{T}} \sum_{a\in A\setminus\{\underset{n\in N}{\cup} D_n\}} c_a^t x_a^t + \sum_{t\in\mathcal{T}} \sum_{a\in\{\underset{n\in N}{\cup} D_n\}} c_a^t (u_a^t - x_a^t) \tag{7}$$

$$\text{s.t.} \quad \sum_{a\in H_n} g_a^t x_a^t - \sum_{a\in T_n} x_a^t = 0 \qquad \forall t\in\mathcal{T}, \forall n\in N\setminus SSN, \tag{8}$$

$$\sum_{a\in H_n} x_a^t - \sum_{a\in T_n} x_a^t = r^t \qquad \forall t\in\mathcal{T}, \forall n\in SSN, \tag{9}$$

$$\sum_{a\in H_n\cap O_n} g_a^t x_a^t - \sum_{a\in T_n\cap O_n} x_a^t = x_{a\in B_n}^{t+1} \qquad \forall t\in\mathcal{T}\setminus\{P\}, \forall n\in N_1, \tag{10}$$

$$x_a^1 = INS_n^1 \qquad \forall n\in N_1, \forall a\in B_n, \tag{11}$$

$$x_a^t = INF_n^t \qquad \forall t\in\mathcal{T}, \forall n\in N, \forall a\in I_n, \tag{12}$$

$$x_a^t \le DEM_n^t \qquad \forall t\in\mathcal{T}, \forall n\in N, \forall a\in D_n, \tag{13}$$

$$0 \le l_a^t \le x_a^t \le u_a^t \qquad \forall t\in\mathcal{T}, \forall a\in A. \tag{14}$$

The objective function (7) minimizes the total costs. Constraint (8) imposes mass conservation flow at all nodes except SSN one. It simply says that the summation of inflows minus outflows at each node should be equal to zero. There is a coefficient for each head arc that represents gain/loss (precipitation/evaporation) process. The system conservation of mass in a node can be: *inflow+precipitation-evaporation-demand+storage* from the previous time period=current level of the water at the end of time t in the reservoir=*storage* at beginning of $t+1$. Constraint (9) controls the overall gain/loss of the water system in each period. In addition, it controls mass conservation flow at SSN. As depicted in Figure 12 the SSN has two system balance arcs and one inflow arc. None of these arcs need any gain/loss coefficient. Constraint (10) keeps track of the storage at reservoirs. In this constraint, the summation of the flows that goes through the reservoir arcs considering their directions identifies the consecutive reservoir storage in following period. Constraint (11) denotes the initial storage at reservoirs in the beginning of the first period. Constraint (12) represents inflows to the nodes. Constraint (13) is the demand constraint and it depicts the maximum amount of water that can flow through the demand arcs. It is defined as a less than equality constraint due to the fact that it allows the model to decide the optimum amount of allocation based on the identified costs. Constraint (14) shows variable domains (bound constraints).

3.3 Experimental results for the deterministic model

3.3.1 An illustrative example

The following water resource system (see Figure 11) is used to illustrate the applicability of the deterministic model. In this system, the river is the main source of water. We assume that the example represents a geographical system in which monthly time scale modeling is acceptable. A water resource manager is responsible to allocate water that comes from the river, then the water goes through the natural channel, and finally reaches to two users (the demand, and the reservoir). The allocation is monthly and the whole system is governed by monthly-dependent operating policies. The aim is to find the planning allocation that has the lowest cost.

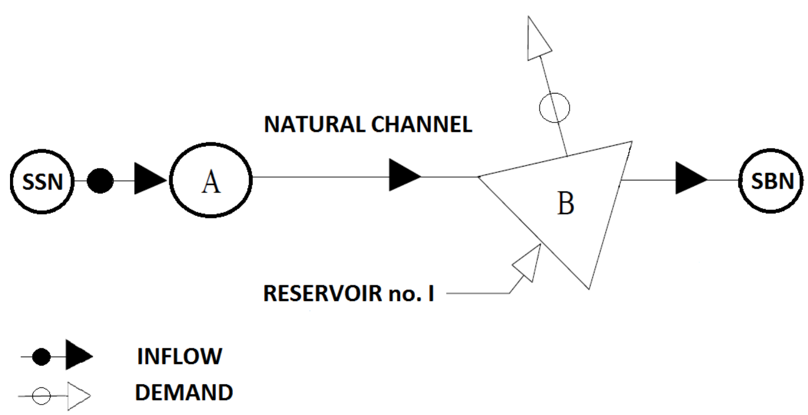

Figure 11: An example of a small water resource system (Example 1)

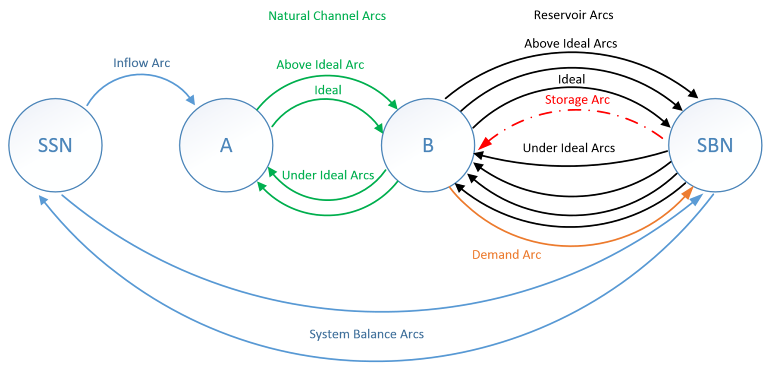

Figure 12: Network flow representation of Example 1

In order to prioritize the allocations, there is a cost associated with each operating policy. Ideal values have the lowest costs and the one with the lowest cost has the highest seniority. Going above or under the ideals increases the cost of allocation. The reservoir has seven rule curves and the natural channel has four operating policies (rule curves).

There is also a target demand for each month and any deviation (deficit) from it will be penalized. Penalties are identified based on per unit of deficit. The water resource manager can only control the trade-off between the demand and the reservoir by changing costs. For the sake of simplicity all levels and storages are converted into "flow equivalenced" storage (for more information see Section 3.1.2 operating policies). As mentioned earlier, there is a level (m) with a specific storage ($liter$) associated with this flow. The third rule curve for the reservoir is called the ideal while the second rule curve for the natural channel is its ideal. Cubic meter per second (m^3/s) is used as the main unit. Time of travel of water in the system is less than a month and the reservoir can be filled up or emptied completely in less than a month. This assumption guarantees practicality of the obtained results. The maximum capacity of the reservoir is equal to the flow of 80 m^3/s. If the water storage in the reservoir goes beyond this value flooding happens and the system will be destroyed.

Figure 12 illustrates the network flow representation of the system. As mentioned earlier, the reservoir has seven rule curves while the natural channel has four rule curves. Figure 13 depicts seven monthly reservoir rule curves. The y-axis presents the amount of "flow equivalenced" based on the m^3/s. The ideal storage value of the reservoir is 30 m^3/s. Any storage value above the rule curve 2 (flooding damage zone) and below the rule curve 6 (drastic shortage zone) should be taken seriously by the decision makers.

Figure 14 shows four monthly natural channel rule curves. The y-axis presents the amount of "flow equivalenced" in terms of m^3/s. The ideal value for the natural channel is 20 m^3/s. The values below the rule curve 3 is deemed dangerous for fish, animals, etc. and flows close the 35 m^3/s increase the risk of flooding in the system.

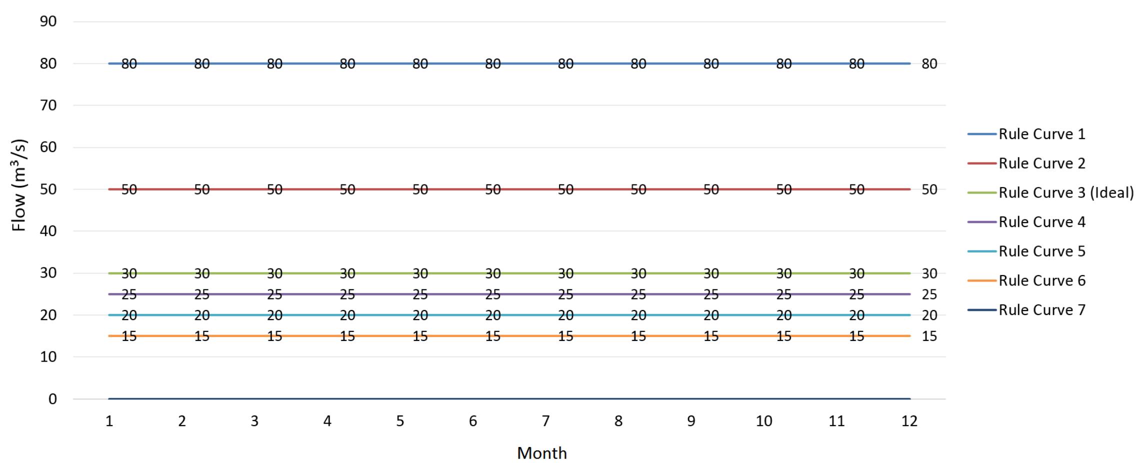

Figure 13: Reservoir rule curves

The distribution of monthly river inflows is shown in Figure 15. The y-axis shows the amount of flow based on the m^3/s. Summer has the highest magnitude of inflow and the peak is on July. Figure 16 shows the distribution of the demand per month. The y-axis presents the amount of flow based on the m^3/s. The demand peak happens on July. The system can be influenced by evaporation/precipitation. Evaporation causes water losses in reservoirs while precipitation leads to adding more water into the system. In this thesis, we combine these two factors and define a new factor called net evaporation/precipitation coefficient. When this coefficient is less than one it means that the system loses water and when it is above one the system gains water. Distribution of monthly net evaporation/precipitation is depicted in Figure 17. The bars above the red line show precipitation while the bars under the red line depict

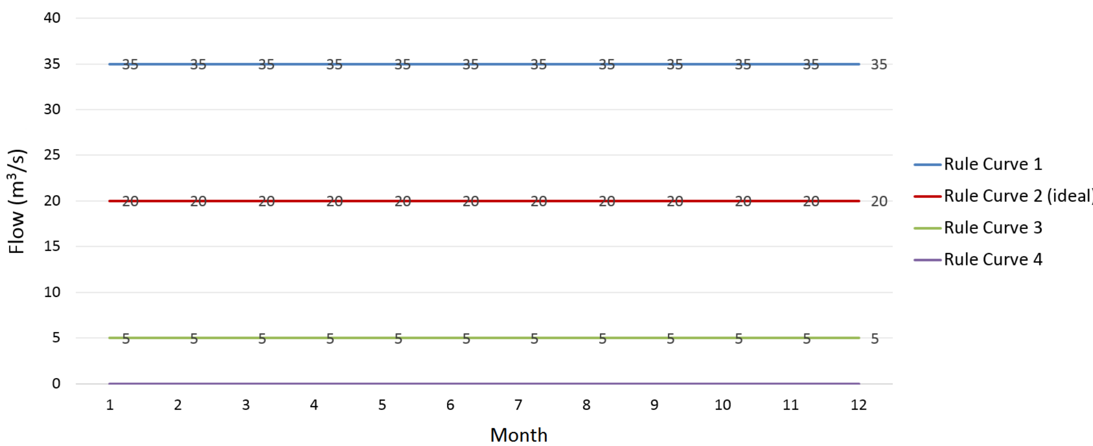

Figure 14: Natural channel rule curves

evaporation. The highest evaporation occurs in summer.

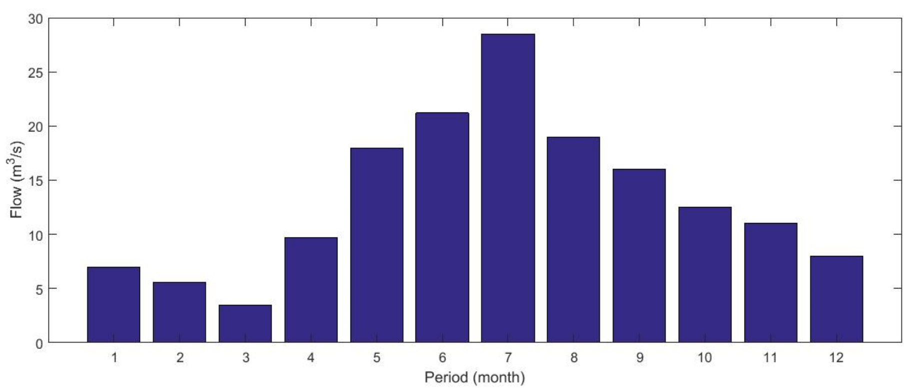

Figure 15: Water river inflows

Finally, the deterministic model in this thesis is coded in optimization programming language (OPL) and solved using CPLEX 12.7, on a PC with 3.50 GHz CPU and 16.00 GB of RAM. Matlab 2016a is used for data visualizations. The time to solve problems to optimality for the deterministic model ranges from 1.5 to 2 seconds.

3.3.2 Design of experiments and results

A number of experiments are designed to show the behavior of the deterministic model under different situations or demonstrate effects of perturbing parameters on

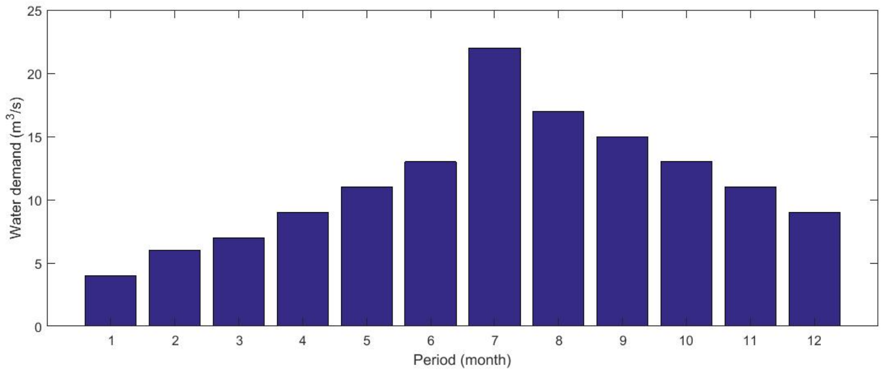

Figure 16: Monthly water demand

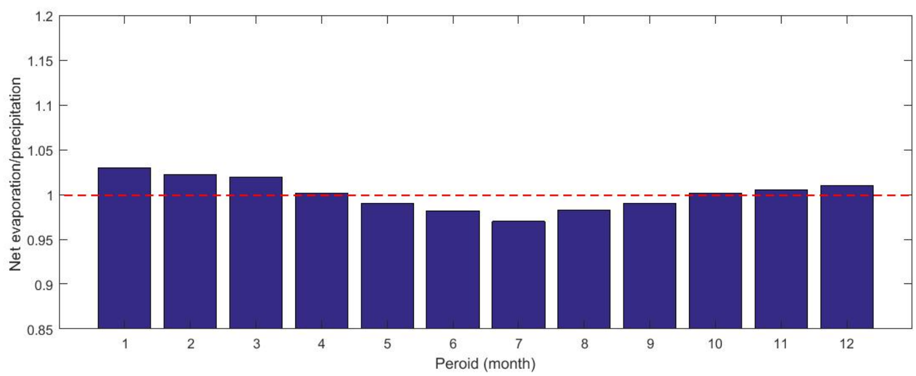

Figure 17: Monthly net evaporation/precipitation

planning results. The set of experiments are:

1. Baseline (status quo)
2. Effect of perturbing the initial storage on the final storage of the reservoir
3. Effect of perturbing penalty (violation cost) of demands on the trade-off between the reservoir's storage and satisfied demands
4. Effect of changing policy (reservoir rule curves) on the trade-off between the reservoir's storage and satisfied demands
5. The shift in the timing of the annual peak of flows in the water system
6. System performance under the effect of evaporation/precipitation

Experiment 1. Baseline (status quo)

In the first experiment, which is also called Baseline (status quo), the water resource system is not affected by any evaporation/precipitation. In this experiment, monthly demands, monthly inflows, and the initial storage of the reservoir are known. Table 1 shows the amount of flows in all system components. The final storage in the reservoir is 46 and the objective function value is 2,219 and all the demands are satisfied. Figure 18 depicts the flows in the system. As seen in Figure 18, the minimum storage of the reservoir is 26.1 and its maximum is 48.5 (always below rule curve 2 depicted in Figure 13). The reservoir storage is above the ideal most of the time.

Table 1: Flows in system components (EXP1)

Period(month)	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Inflow(m^3/s)	-	7.0	5.6	3.5	9.7	18.0	21.2	28.5	19.0	16.0	12.5	11.0	8.0
Natural channel flow(m^3/s)	-	7.0	5.6	3.5	9.7	18.0	21.2	28.5	19.0	16.0	12.5	11.0	8.0
Reservoir storage(m^3/s)	27.0	30.0	29.6	26.1	26.8	33.8	40.0	45.5	47.5	48.5	47.0	47.0	46.0
Ideal storage for the reservoir(m^3/s)	-	30	30	30	30	30	30	30	30	30	30	30	30
Ideal storage for the channel(m^3/s)	-	20	20	20	20	20	20	20	20	20	20	20	20
Actual demand(m^3/s)	-	4	6	7	9	11	15	23	17	15	14	11	9
Satisfied demand(m^3/s)	-	4	6	7	9	11	15	23	17	15	14	11	9

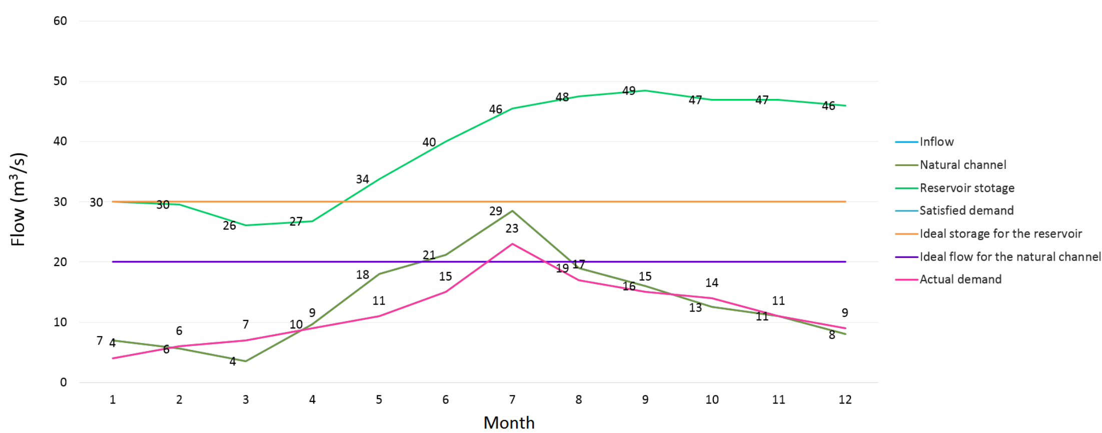

Figure 18: Graphical representation of flows in the system (EXP1)

Experiment 2. Effect of perturbing the initial storage on the final storage of the reservoir

In the second experiment, the magnitude of the initial storage in the reservoir is perturbed and the value of the other parameters kept the same as the Baseline. Initial storage varies between 3 to 29. Table 2 depicts the amount of final storages, unmet demands, and objective function values. Increasing the initial storage from 3 to 13 led to augment the satisfied demand. Increasing its value from 14 to 19 doest not affect the unmet demand while causes the final reservoir storage to increase. Again increasing the initial storage value from 20 to 24 decreases the unmet demand to zero. The first three months are the most affected ones by the initial storage perturbations. As the initial storage increases, the unmet demand for the third month reduces. This reduction follows for the second month, and the third month, respectively. Therefore, the first three months are more vulnerable than others. The box-plot (see Figure 19) displays the monthly variations reservoir storage. The zero month shows initial storage alterations. As shown in Figure 19 the fluctuations of the first three months are greater and in both directions owing to having low magnitudes of inflow in the first three months.

Table 2: Effect of perturbing the initial storage on the final storage of the reservoir and unmet demand (EXP2)

Initial storage(m^3/s)	3	4	5	6	7	8	9	10	11
Objective function value	2568.1	2541.1	2514.1	2487.1	2460.1	2441.1	2423.1	2405.1	2387.1
Final reservoir storage(m^3/s)	36	36	36	36	36	36.4	36	36	36
Unmet demand(m^3/s)	14	13	12	11	10	9.4	8	7	6

Initial storage(m^3/s)	12	13	14	15	16	17	18	19	20
Objective function value	2369.1	2351.1	2334.7	2319.5	2304.5	2290.4	2277.4	2266	2255.8
Final reservoir storage(m^3/s)	36.4	36.4	37	38	39	40	41	42	42.2
Unmet demand(m^3/s)	5.4	4.4	4	4	4	4	4	4	3.2

Initial storage(m^3/s)	21	22	23	24	25	26	27	28	29
Objective function value	2245.8	2235.8	2225.8	2222.2	2220.2	2219.1	2219.1	2233.5	2253
Final reservoir storage(m^3/s)	42.2	42.2	42.2	43	44	45	46	47	48
Unmet demand(m^3/s)	2.2	1.2	0.2	0	0	0	0	0	0

Experiment 3. Effect of perturbing penalty (violation cost) of demands on the trade-off between the reservoir's storage and satisfied demands

In this experiment, the demand penalties are altered to demonstrate the behavior of the model under different costs. The initial storage of the reservoir is 14 and penalty

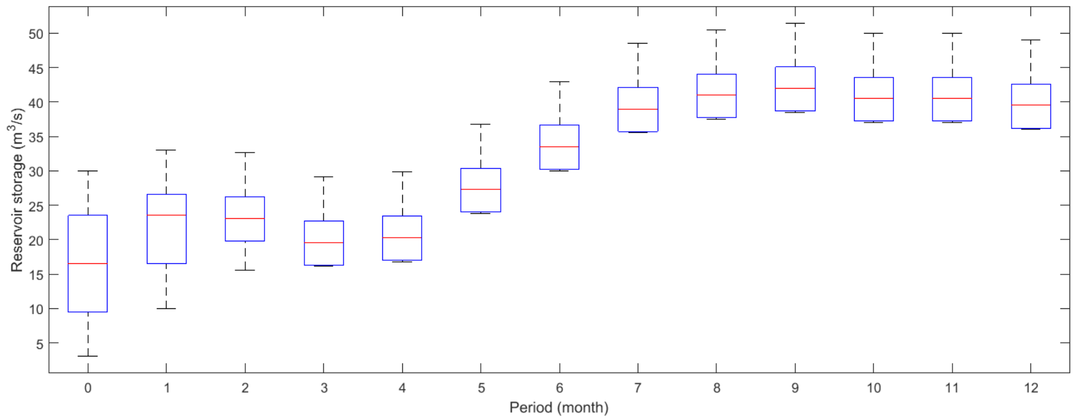

Figure 19: Graphical representation of the effect of perturbing the initial storage on the final storage of the reservoir (EXP2)

values changes from 0 to 32. Table 3 shows the results of the third experiment. When the penalty is very low unmet demand reaches to its highest value which is 9.2 m^3/s. In general, increasing penalty values for the demand leads to decrease unmet demands. But between some ranges the system is stable and the unmet demand does not alter (i.e., penalty value between 10 to 15). The reason is that in the trade-off between the reservoir and the demand when there is a severe water shortages the cost of not meeting demand is less than the cost of emptying the reservoir.

Table 3: Effect of perturbing penalty on the final reservoir storage and unmet demands (EXP3)

Demand penalty(m^3/s)	0	1	2	3	4	5	6	7	8	9	10
Objective function value	2259	2268.2	2277.4	2286.6	2295.8	2305	2313.4	2320.3	2326.5	2330.7	2334.7
Final reservoir storage(m^3/s)	42.2	42.2	42.2	42.2	42.2	42.2	39.9	39.2	39.2	37.2	37
Unmet demand(m^3/s)	9.2	9.2	9.2	9.2	9.2	9.2	6.9	6.2	6.2	4.2	4

Demand penalty(m^3/s)	11	12	13	14	15	16	17	18	19	20	21
Objective function value	2338.7	2342.7	2346.7	2350.7	2354.7	2358.7	2362.1	2365.1	2368.1	2371.1	2374.1
Final reservoir storage(m^3/s)	37	37	37	37	37	36.4	36	36	36	36	36
Unmet demand(m^3/s)	4	4	4	4	4	3.4	3	3	3	3	3

Demand penalty(m^3/s)	22	23	24	25	26	27	28	29	30	31	32
Objective function value	2377.1	2380.1	2383.1	2386.1	2389.1	2392.1	2394	2395.2	2395.2	2395.2	2395.2
Final reservoir storage(m^3/s)	36	36	36	36	36	36	34.9	34.2	33	33	33
Unmet demand(m^3/s)	3	3	3	3	3	3	1.9	1.2	0	0	0

Experiment 4. Effect of changing policy (reservoir rule curves) on the trade-off between the reservoir's storage and satisfied demands

In this experiment, the magnitude of the ideal rule curve of the reservoir changes from 30 m^3/s to 25 m^3/s. The initial storage is 14. Table 4 shows the result of perturbing penalty while having a new policy. As seen in Table 4, decreasing the ideal value by five units leads to deceasing the unmet demand compared to the third experiment (see Table 3). The unmet demand reaches zero value with the penalty equal to 16 while in the third experiment the penalty value should be 30 to have zero unmet demand. In general, decreasing the ideal for the reservoir is equal to decrease the satisfaction level for the reservoir. As a result, less water is allocated in the reservoir and the remaining goes to the demand. However, the unmet demand reductions pattern is similar to a piecewise linear function.

Table 4: Effect of changing policy on the final storage of the reservoir and unmet demands (EXP4)

Demand penalty(m^3/s)	0	1	2	3	4	5	6	7	8
Objective function value	2165	2169.2	2173.4	2177.6	2181.8	2186	2190	2194	2198
Final reservoir storage(m^3/s)	37.2	37.2	37.2	37.2	37.2	37.2	37	37	37
Unmet demand(m^3/s)	4.2	4.2	4.2	4.2	4.2	4.2	4	4	4
Demand penalty(m^3/s)	9	10	11	12	13	14	15	16	17
Objective function value	2202	2206	2210	2213.4	2216.4	2218.3	2219.5	2219.5	2219.5
Final reservoir storage(m^3/s)	37	37	36.4	36	36	34.2	34.2	33	33
Unmet demand(m^3/s)	4	4	3.4	3	3	1.2	1.2	0	0

Experiment 5 The shift in the timing of the annual peak of flows in the water system

The performance of the majority of water resource systems is highly dependent on the natural flow regime. Climate change can affect the timing of the annual peak of flows in the water system, magnitude of the peak, or both. It also can drastically change the whole distribution of the natural flow regime. In this experiment, we analyze the performance of the system assuming that the distribution of the inflow does not change and only one month shift occurs. Thus the purpose of this experiment is to test the performance of the current water resource system under the shift in the timing of the annual peak. To do so, we shift the inflow one month to the right and the left and evaluate the planning results. The Baseline is selected for this test and the demand and the cost values are stable.

Table 5 depicts the results of the one month shift to the right for the inflow. The objective value function is equal to 2134.5 and there is an unmet demand for the fourth month with the magnitude of 1.2 m^3/s. Therefore, the system is vulnerable to the right shift in the timing of the annual peak.

Figure 20 depicts the graphical representation of the effect of shift to the right on the flows in system components. As shown in Figure 20, the reservoir storage fluctuates around the ideal line. It is also under the ideal for four times. The blue numbers in Figure 20 represents the satisfied demand. The pink line shows the actual demand. As can be seen in Figure 20, the shift in the timing of the peak happens in the eight month (follow the dark green line) and based on the results, one concludes that the one month shift has an impact on the system.

Table 5: The effect of shift to the right on the flows in system components (EXP5)

Period(month)	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Inflow(m^3/s)	-	8.0	7.0	5.6	3.5	9.7	18.0	21.2	28.5	19.0	16.0	12.5	11.0
Natural channel flow(m^3/s)	-	8.0	7.0	5.6	3.5	9.7	18.0	21.2	28.5	19.0	16.0	12.5	11.0
Reservoir storage(m^3/s)	27.0	31.0	32.0	30.6	26.3	25.0	28.0	26.2	37.7	41.7	43.7	45.2	47.2
Ideal storage for the reservoir(m^3/s)	-	30	30	30	30	30	30	30	30	30	30	30	30
Ideal storage for the channel(m^3/s)	-	20	20	20	20	20	20	20	20	20	20	20	20
Actual demand(m^3/s)	-	4	6	7	9	11	15	23	17	15	14	11	9
Satisfied demand(m^3/s)	-	4	6	7	7.8	11	15	23	17	15	14	11	9

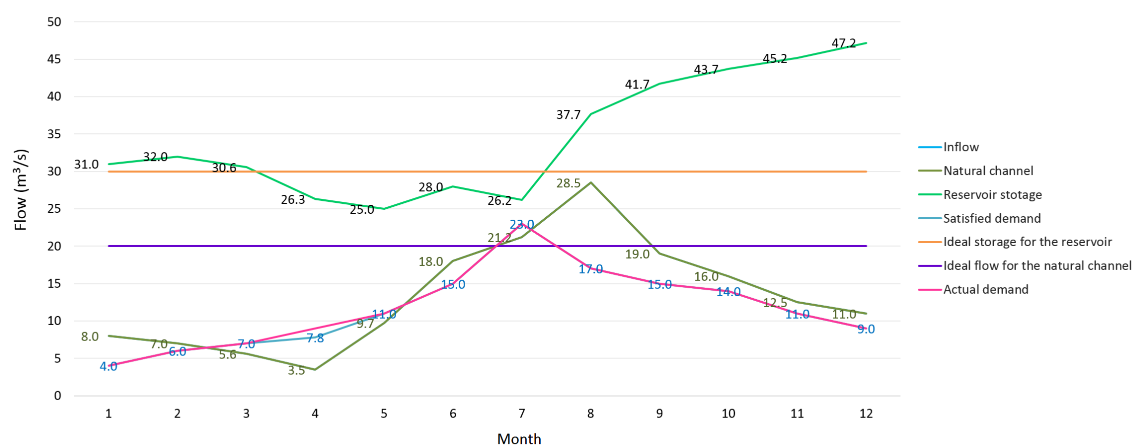

Figure 20: Graphical representation of the effect of shift to the right on the flows in system components

Table 6 shows the results of the one month shift to the left for the inflow. The objective value function is equal to 2529.6 and there is not any unmet demand. Figure 21 depicts the graphical representation of the effect of shift to the right on the flows in system components. As shown in Figure 21, the reservoir storage decreases in the second month, then increases for four consecutive months (reaches to its maximum level which is 61.5 m^3/s), next reduces for a couple of months, and finally becomes 46 m^3/s. The shift in the timing of the peak happens in the six month (follow the dark green line). There is not any unmet demand, but the reservoir storage for four months is above the rule curve 2 (see Figure 13). It is a sign for flood risk in the system. Ergo, the system is vulnerable to the left shift in the timing of the annual peak.

Table 6: The effect of shift to the left on the flows in system components (EXP5)

Period(month)	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Inflow(m^3/s)	-	5.6	3.5	9.7	18.0	21.2	28.5	19.0	16.0	12.5	11.0	8.0	7.0
Natural channel flow(m^3/s)	-	5.6	3.5	9.7	18.0	21.2	28.5	19.0	16.0	12.5	11.0	8.0	7.0
Reservoir storage(m^3/s)	27.0	28.6	26.1	28.8	37.8	48.0	61.5	57.5	56.5	54.0	51.0	48.0	46.0
Ideal storage for the reservoir(m^3/s)	-	30	30	30	30	30	30	30	30	30	30	30	30
Ideal storage for the channel(m^3/s)	-	20	20	20	20	20	20	20	20	20	20	20	20
Actual demand(m^3/s)	-	4	6	7	9	11	15	23	17	15	14	11	9
Satisfied demand(m^3/s)	-	4	6	7	9	11	15	23	17	15	14	11	9

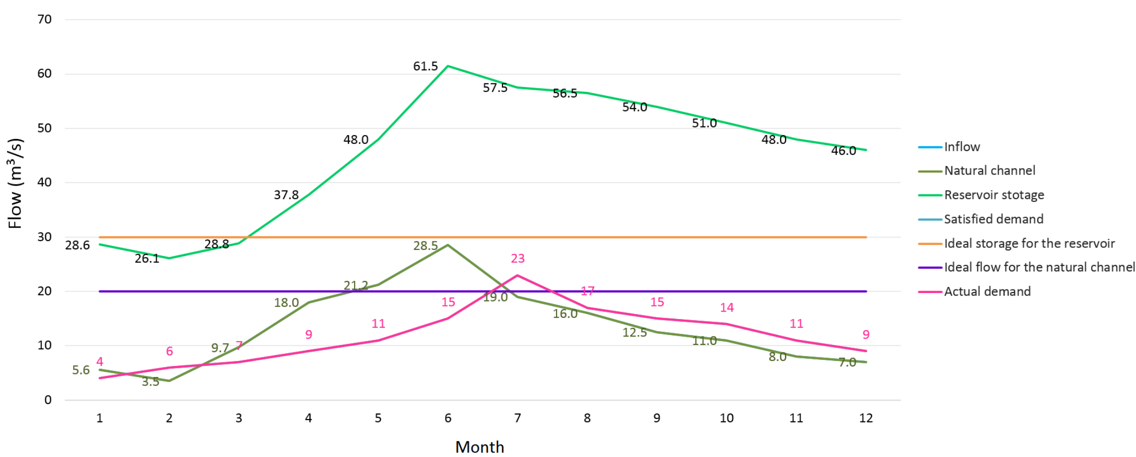

Figure 21: Graphical representation of the effect of shift to the left on the flows in system components

Experiment 6. The effect of evaporation/precipitation on the system

Evaporation/precipitation has an impact on plenty of water resource systems. For example, evaporation from open reservoirs leads to water loss. Additionally, changes in precipitation (pattern, intensity, etc.) can also affect water resource systems. As the reservoir is one of the most important components of this system, in this experiment, we assess the system performance under evaporation/precipitation of the reservoir. We assume that the net evaporation/precipitation value for all arcs of the reservoir in one month is the same. More precisely, the reservoir storage level affects the evaporation/precipitation in a linear way. We run the experiment using the input data shown in Figure 17.

Table 7 depicts the amount of flows in all system components. The final storage in the reservoir is 45.1 and the objective function value is 2,193.5 and all the demands were satisfied. Figure 22 shows the flows in the system. As shown in Figure 22, the minimum storage of the reservoir is 28.3 and its maximum is 46.9 (always bellow the rule curve 2). Based on the obtained results, one concludes that evaporation/precipitation affects the system, however, does not make the system vulnerable.

Table 7: The effect of evaporation/precipitation on the system (EXP6)

Period(month)	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Inflow(m^3/s)	-	7.0	5.6	3.5	9.7	18.0	21.2	28.5	19.0	16.0	12.5	11.0	8.0
Natural channel flow(m^3/s)	-	7.0	5.6	3.5	9.7	18.0	21.2	28.5	19.0	16.0	12.5	11.0	8.0
Reservoir storage(m^3/s)	27.0	30.9	31.2	28.3	29.0	35.7	41.1	45.2	46.4	46.9	45.5	45.7	45.1
Ideal storage for the reservoir(m^3/s)	-	30	30	30	30	30	30	30	30	30	30	30	30
Ideal storage for the channel(m^3/s)	-	20	20	20	20	20	20	20	20	20	20	20	20
Actual demand(m^3/s)	-	4	6	7	9	11	15	23	17	15	14	11	9
Satisfied demand(m^3/s)	-	4	6	7	9	11	15	23	17	15	14	11	9

3.4 Discussion

The aim of this chapter is to develop a deterministic mathematical model for water resource system planning at river basins. We propose a general network flow model with multiple arcs to model the water resource system with different operating policies in river basin. Multiple arcs are helpful owing to their role in creating a piecewise linearized function of costs/priorities. We also explain how to model distinct components of river basin systems. To demonstrate the behavior of the model a set of experiments are conducted on an artificial river basin water resource system.

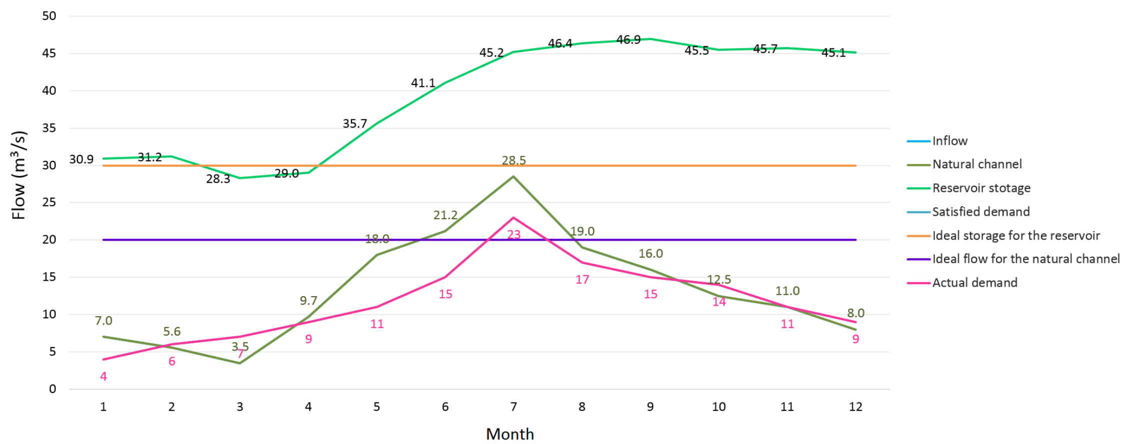

Figure 22: Graphical representation of the effect of evaporation/precipitation on the flows in system components (EXP6)

In the first experiment which is also called Baseline we solve the deterministic model under no evaporation/precipitation. The results show that the system is fully functional and all the demands are satisfied.

In the second experiment, the effect of perturbing the initial storage on the final storage of the reservoir is tested. In general, increasing the value of the initial storage level has an effect on reducing the unmet demand. For our system, the unmet demand reduction pattern follows a piecewise linear function.

In third one, we perturb penalty (violation cost) of demands to examine its influence on the trade-off between the reservoir's storage and satisfied demands. Generally, increasing penalty values for the demand leads to decrease unmet demands. The unmet demand reduction shape behaves as a piecewise linear function.

The fourth experiment is regarding effect of changing policy (reservoir rule curves) on the trade-off between the reservoir's storage and satisfied demands. Having lower ideal value for the reservoir leads to better meeting demand. The reason is that reducing the magnitude of the ideal rule curve for the reservoir is equal to decreasing the satisfaction level for the reservoir. As a result, the reservoir gains its required water with lower value and the remaining water goes to the demand. The unmet demand decreases similar to a piecewise linear function.

In the fifth experiment, we are interested to assess the possible impact of climate change on the system. Thus, the shift in the timing of the annual peak of flows is examined. The shift can be either to the left or to the right. The system is vulnerable in both experiments.

To have a better understanding of the model, system performance under effect of evaporation/precipitation is tested in experiment 6. The results indicate that the system is fully functional and there are no shortages.

3.5 Conclusions

In this chapter, a deterministic mathematical model is developed for water resource system planning. This model is a network flow model with the objective function that seeks to find the minimum cost allocation plan. To model different priorities in the river basin and creating a piecewise linearized function of costs/priorities multiple-arcs are used.

In order to better understand the behavior of the water resource planning model, we conduct a set of experiments. The problem is solved for a different range of parameter values. The planning results are compared and the trade-off between reservoir storage and demand satisfaction is analyzed. To assess the possible impact of climate change on the system, we also test model performance under the effect of shift in the timing of the annual peak and show that the model is vulnerable under both right and left shift.

Further work includes incorporating other components of water river basins such as hydropower plants, apportionment channels, etc. into the mathematical model. Furthermore, using this approach to model a real water river basin that is already modeled by a software and comparing them is suggested.

Chapter 4

Robust decision making water resource planning model

In this chapter, we employ robust decision making approach for water resource planning under deep uncertainty. The same water resource system as in Chapter 3 is used for analyzing the system performance under evaporation/precipitation uncertainty. We demonstrate the applicability and value of using RDM analysis through a set of experiments. This chapter shows the importance and value of using RDM analysis for managing river basin systems under deep uncertainty. MADM approach is also used in RDM analysis for evaluating alternatives and selecting the most robust strategy.

4.1 RDM analysis

The aim of this experiment is to use RDM to deal with evaporation/precipitation uncertainty. In particular, the ultimate goal of this approach in this chapter is to evaluate two different operating policies with respect to uncertainty and further compare the two in order to choose which of them is better using MADM. To do so, we use the "XLRM Matrix" introduced by Lempert, Popper, and Bankes (2003) [111]. The XLRM Matrix has four main boxes that are defined for RDM analysis. The boxes include uncertain factors or uncertainties (Xs) that identify the futures; the management decisions, options, or levers (Ls) that depict the alternative strategies; the performance metrics (Ms) that are used to assess outcomes; and the relationships or models (Rs) that are employed to manage the water resource system (see Table 8).

Table 8: XLRM Matrix reflecting the example

Uncertainties (X)	**Decisions, Options, or Levers (L)**
Climate conditions	1) Current policy 2) New policy
Relationships or Models (R)	**Performance Metrics (M)**
Current deterministic water resource management model	Reliability,Vulnerability,Resilience, and Sustainability.

Future projections

To run the experiments and assess the system performance, one needs to have future projections (Xs) of the desired system. Future projections represent the future of the current system and they are frequently different with each other. In practice, scholars use general circulation model for this purpose. Here, we assume that due to the climate change the future is more dry. As the future is highly uncertain and the current distribution may change, fitting a distribution on the available data and using this distribution to take samples may not be a good approach. We know that stationary assumptions may not be valid in water planning problems [136] and means and variances of future distributions will change over time (for more information see Section 2.1.1 water resource systems definitions and characteristics). In traditional scenario planning decision makers use samples taken from fitted distributions to describe what the future brings. RDM uses sampling in a different way. In this approach decision makers do not concentrate on the likelihood of different futures. The samples are taken without making judgments about whether one future is more likely than any other. Based on Groves et al. in RDM "analysts sample uniformly across the range of plausible values to ensure that all viewpoints about the future are represented, but are not judging whether one sample is more likely than another" [69, p. 9].

We use the uniform distribution for evaporation/precipitation in each month. The months are assumed to be independent. We generate some future ranges for the precipitation/evaporation of the reservoir (Xs). The future projection of precipitation/evaporation values are depicted in Figure 23. To have a balanced generated data, for seven months the range is inclined toward being dryer. However, for the other months the generated range is equally distributed between dryer and wetter conditions. Simply, the probability of having a dryer future is the same as having a wetter future. The red lines show the past data (used in EXP6) and the boxplot depicts the future ranges of precipitation/evaporation of the reservoir. As shown in Figure 23, the future is more dryer and warmer.

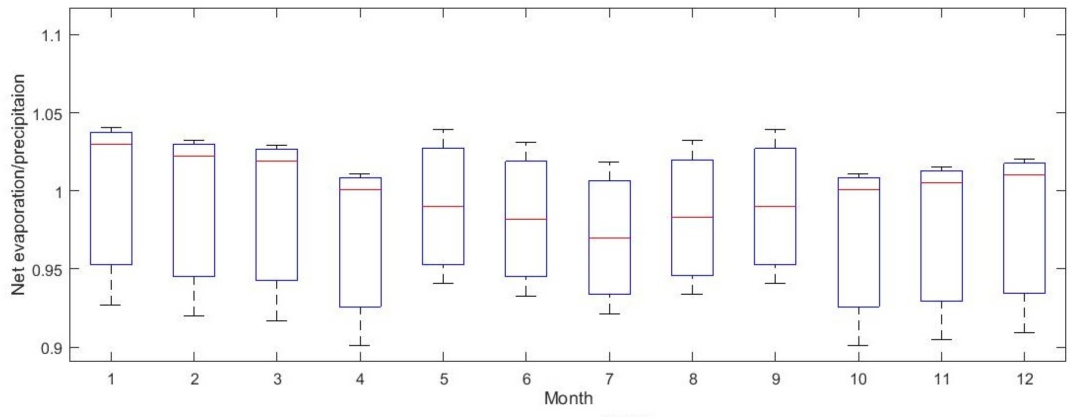

Figure 23: Graphical representation of monthly future range for evaporation/precipitation (EXP5)

Performance metrics

In order to conduct the vulnerability assessment fifty samples are taken from the monthly net evaporation/precipitation distribution using Monte-Carlo simulation. Four common performance metrics for vulnerability assessment are as follows.

1. Reliability: This criteria describes how likely the system is to fail [77]. It can be calculated as dividing the number of months that the system can meet all demands and no shortage occurs by the total number of months in percentage. The meaning of a reliability of one hundred percent is that no shortages happen in a simulation [134].

2. Vulnerability: This criterion states how severe the consequences of failure might be [77]. It is equal to the percent of unsatisfied demand when there is a shortage. This factor gauges the mean depth of shortage across the projection in percentage scale for those years with shortages [80, 32]. To be able to have the same scale similar to other factors, we uses the inverse ("1-Vulnerability") which quantifies the average percent met demand when shortage happens.

3. Resilience: This measure explains how quickly the system recovers from failure [77]. How many times a shortage month is followed by a non-shortage month? This index determines the system's ability to recover from a previous shortage [141].

4. Sustainability: An overall sustainability index is identified by Sandoval-Solis et al. [156] using the unweighted geometric mean of the former three indices (15):

$$Sustainability = (Reliability * (1 - Vulnerability) * Resilience)^{1/3} \tag{15}$$

Evaluation of the system performance under the current policy

Figure 24 shows Monte-Carlo simulation results. Each point in the scatterplot depicts the system performance results under that future, including Reliability (x-axis), 1-Vulnerability (y-axis), and Resilience (color range). In each future, the deterministic water resource model allocates water in the river basin and if there is not any shortage, the system is considered functional. As the water allocation is monthly, the total number of months in the simulation is equal to $50 \times 12 = 600$.

There are 37 overlapping points in reliability of 100, 1-Vulnerability of 100, and Resilience of 100, located in the top right corner of Figure 24. This very bright yellow point represents $37 \times 12 = 444$ months out of 600 months without any delivery shortage, and with 100% 1-Vulnerability, and 100% Resilience. It means that the system is perfectly functional in 37 futures out of 50 simulated futures.

There are two yellow points approximately located in the middle of Figure 24, that are very close to each other. Each point represents two overlapping system results under two futures. The left one illustrates one point for two futures with Reliability of 92%, 1-Vulnerability 71.9%, and 88% Resilience. The right one shows one point for two futures with Reliability of 92%, 1-Vulnerability 72.5%, and 88% Resilience. Each of the two bright orange points in the bottom left corner represents the system performance under a simulated future: one with Reliability of 75%, 1-Vulnerability 61%, and 67% Resilience, and another with Reliability of 75%, 1-Vulnerability 62%, and 67% Resilience. The four orange points under the yellow points and above the light orange ones illustrate the system performance under four futures with 83% Reliability, 1-Vulnerability 64%, 67%, 71%, and 79%, and 50% Resilience. Based on the obtained simulation results, the minimum Reliability of the system under simulated futures is 75%, and the minimum 1-Vulnerability of the system is 61% having the assumption that the demand and the inflow values are known.

There are 21 out of 600 months that experience shortages. The frequency of the occurrence of shortages in each month is: 13 times for the second month, 6 times for the third month, 2 times for the eleventh month, and zero for the others. It simply means that if shortages happen the probability of occurring shortages for the second, the third, and the eleventh month is: 61.9%, 28.6%, and 9.5%. Using this information, one concludes that these three months have a profound impact on the system performance.

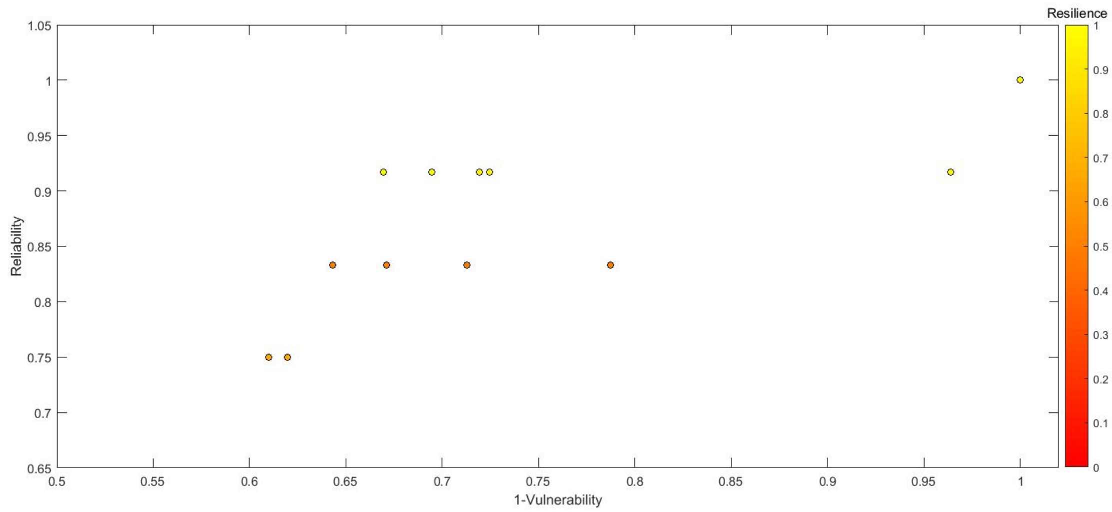

Figure 24: Graphical representation of the system performance for the current policy

Table 9 shows the system performance results for fifty samples. The first column depicts performance metrics. Colors are scaled from 0 to 100 percent. The color rules are: values above 80% are colored green, values between 75% to 80% are colored yellow, values between 75% to 70% are colored orange, and values below 70% are colored red. The results depict that the system overall Reliability is 97% under different futures. Reliability exceeds 95%; the performance of the 1-Vulnerability, Resilience, and Sustainability metrics is not satisfying with values being 69 percent, 71 percent, and 78 percent respectively. The system would expect a shortage level of nearly 31 percent of demand when shortages occur. It is important to note that in this set of experiments only one uncertain climate related factor is studied. The performance might be worsen if other factors, such as changes in the magnitude and timing of the annual peak or demand are selected as uncertain parameters.

Table 9: Performance metrics results for the system (the current policy)

	Baseline	Current policy under future change in the evaporation/precipitation
Reliability	100%	97%
1-Vulnerability	100%	69%
Resilience	100%	71%
Sustainability	100%	78%

Evaluation of the system performance under the new policy

As the system performance is not satisfying, we are interested to assess the system performance considering a "new policy" under future uncertainties. The new policy is defined as changing the magnitude of the ideal rule curve of the reservoir from 30 m^3/s to 25 m^3/s (the same as EXP4). We assume that this shift is possible. In order to have a fair comparison, we use the same fifty Monte-Carlo samples for testing the new strategy.

Figure 25 displays Monte-Carlo simulation results for the new policy. Each point in the scatterplot depicts the system performance results under that future, including Reliability (x-axis), 1-Vulnerability (y-axis), and Resilience (color range). In each future, the deterministic water resource model allocates water in the river basin and if there is not any shortage, the system is considered functional. As the water allocation is monthly, the total number of months in the simulation is equal to $50 \times 12 = 600$.

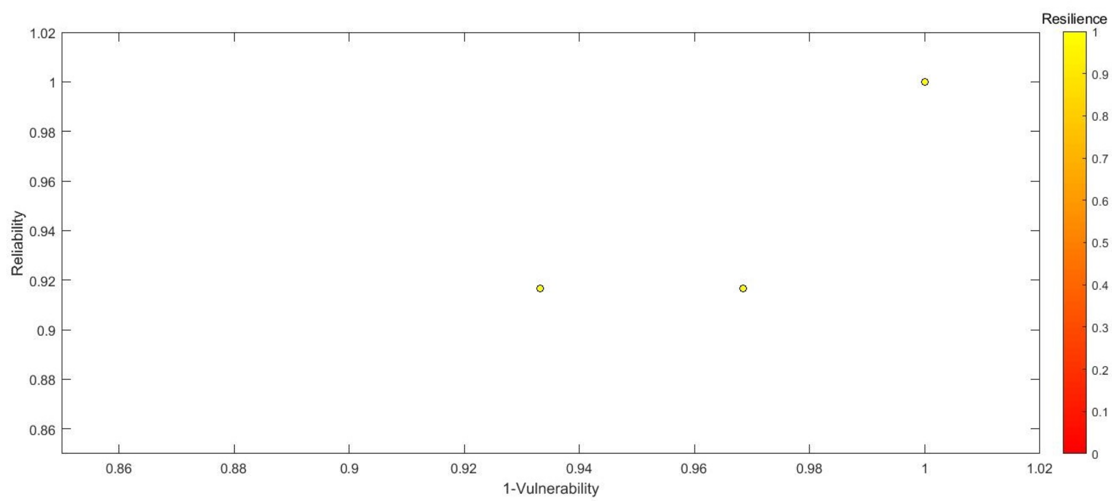

Figure 25: Graphical representation of the system performance for the new policy

There are 48 overlapping points in reliability of 100, 1-Vulnerability of 100, and

Resilience of 100, located in the top right corner of Figure 25. This top-right point represents $48 \times 12 = 576$ months out of 600 months without any delivery shortage, and with 100% 1-Vulnerability, and 100% Resilience. It means that the system is perfectly functional in 48 futures out of 50 simulated futures.

The one yellow point in the left (see Figure 25) displays the system performance under a future with Reliability of 92%, 1-Vulnerability 93%, and 100% Resilience. The yellow point in the right shows the system performance under a future with Reliability of 92%, 1-Vulnerability 97%, and 100% Resilience. Based on the simulation results, the minimum Reliability of the system under different futures is above 92%, and the minimum 1-Vulnerability of the system is 93% having the assumption that the demand and the inflow values do not alter in the future.

There are 2 months out of 600 months when the system experiences shortages. The frequency of the occurrence of shortages for each month is: 2 times for the third month, and zero for others. It simply means the probability of shortages in month 3 appears higher than in other months. Using this information, one concludes that the third month has a profound impact on the overall system performance.

Table 10 shows the overall system performance results for Monte-Carlo simulation having the new policy (the new policy is defined as changing the magnitude of the ideal rule curve of the reservoir from 30 m^3/s to 25 m^3/s). Colors are scaled from 0 to 100 percent with the same rules as in Table 9. The results depict that Reliability is 99.67% under different futures. Reliability exceeds 95 percent; performance of the 1-Vulnerability, Resilience, and Sustainability metrics is acceptable being 95%, 100%, and 98% respectively. The system would expect a shortage level of nearly 5% of demand when shortages occur. It is worth mentioning that in this set of experiments only one uncertain climate related factor is studied. The performance might be worsen if other factors, such as changes in the magnitude and timing of the annual peak or demand growth are selected as uncertain parameters.

Table 10: Performance metrics results for the system (the new policy)

	Baseline	New policy under future change in evaporation/precipitation
Reliability	100%	99.67%
1-Vulnerability	100%	95%
Resilience	100%	100%
Sustainability	100%	98%

MADM analysis

The two above strategies have differing performance in different metrics – in this section, we use MADM to compare the two alternatives and choose the best one, incorporating the four criteria defined above.

Simple additive weighting (SAW) method

RDM approach has a step called trade-off analysis. In this step a group of experts analyze strategies to select the best one. In order to be able to choose an alternative amongst a set of alternatives one needs to evaluate them considering different criteria. Thus the question is how to select the best robust strategy strategy from a set of alternatives having multiple, often conflicting criteria.

To answer this question we use one of the simplest, but famous MADM methods, namely simple additive weighting (SAW). SAW is introduced by Churchman and Ackoff (1954) [39] for decision making with multiple criteria. It is based on the idea that an optimum decision is dependent on two factors: (1) How much effect an alternative has on an outcome considering a specific criterion? (2) How much is the weight of that criteria? Thus the alternative that maximizes the expected total weighted effect is optimum. For more details about SAW the reader is refer to the sources [4, 181].

The first step in SAW analysis is to create the initial decision making matrix which is made of evaluation criteria and alternatives. For choosing the most appropriate criteria, we use the four performance metrics defined above, plus minimum reservoir level, maximum reservoir level, and the ratio of the new ideal value for the reservoir to the ideal reservoir level in the Baseline. The minimum and the maximum reservoir level is selected from all simulated samples. Then, the initial decision matrix is filled out using quantitative data from the obtained results (see Table 11). The first column shows the alternatives and the other columns depict the evaluation criteria. Each cell displays an evaluation value for an alternative with respect to a specific criterion. We are aware of the fact that the Sustainability criterion is made of the three other criteria (Reliability, 1-Vulnerability, and Resilience) and thus is dependent on them. While such dependence might bias the results of the SAW method, we later show via sensitivity analysis that our results hold even when the weight of the Sustainability is low.

Table 11: The initial decision making matrix

Alternative	Reliability	1-Vulnerability	Resilience	Sustainability	Min	Max	Current Ideal/Baseline ideal
Current policy	0.965	0.692	0.714	0.781	17.530	47.987	1.000
New policy	0.997	0.951	1.000	0.982	17.278	48.205	0.833

The second step is to normalize the decision making matrix values. As each criterion has a different unit, the evaluations should be normalized. Without normalization it is not possible to do the arithmetic operators or do any comparison. To convert all the criteria values into non-dimensional ones using SAW method, each criteria is classified into benefit criterion (the greater the better) or cost criterion (the smaller the better). In this thesis, the maximum reservoir level is a cost criteria. The reason is that the maximum reservoir level is a sign for flooding and we prefer to have an alternative with lower value of this criterion. The other criteria belong to benefit criteria group due to the fact that having an alternative with greater value in any of them is more preferable. For each benefit criterion, we divide each evaluation by the maximum value of that specific column. For each cost criterion, we divide the minimum value of that specific column by each evaluation. Using this normalization, numbers range between zero to one. Table 12 displays the normalized decision making matrix.

Table 12: The normalized decision matrix

Alternative	Reliability	1-Vulnerability	Resilience	Sustainability	Min	Max	Current Ideal/Baseline ideal
Current policy	0.968	0.728	0.714	0.795	1.000	1.000	1.000
New policy	1.000	1.000	1.000	1.000	0.986	0.995	0.833

Calculating weights for the normalized decision matrix

In order to rank the alternatives in SAW analysis, one needs to have the weight of each criterion. The weights are usually identified by a group of experts. As in this thesis we do not have access to any water resource manager, we assume that all criteria have the same weights. Thus, the weight of each criterion is equal to $1/7 = 0.143$ and their summation is 1. After identifying criteria weights, each normalized evaluation should be multiplied by its associated criterion weight. Finally, by summing all values in each row the score of each alternative is calculated. Table 13 displays the weighted normalized decision making matrix and the last column shows the score of each alternative. As shown in Table 13, new policy has a higher overall score which means that it is more robust.

Figure 26 represents the performance of each policy compared with the other one

Table 13: The weighted normalized decision making matrix

Alternative	Reliability	1-Vulnerability	Resilience	Sustainability	Min	Max	Current Ideal/Baseline ideal	Score
Current policy	0.138	0.104	0.102	0.114	0.143	0.143	0.143	0.887
New policy	0.143	0.143	0.143	0.143	0.141	0.142	0.119	0.973

considering criteria. The red line depicts new policy and the blue line shows the current policy. As shown in Figure 26, the new policy has a better performance compared with the current policy in four criteria while the performance of the current policy is better in three criteria.

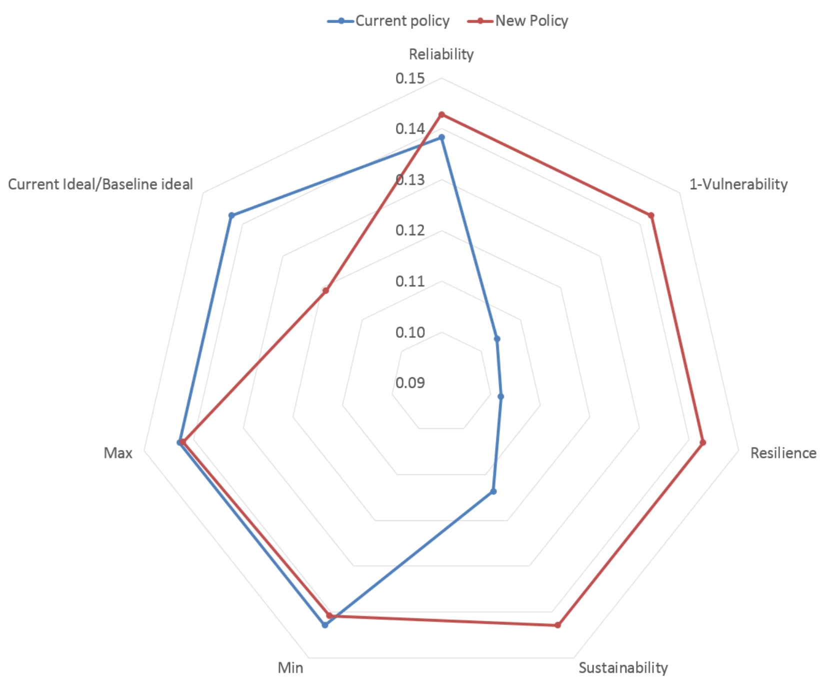

Figure 26: Spider chart representing the performance results for policies

Sensitivity analysis

In this thesis, we assume that the criteria weights are equal. Additionally, we know that weights have an effect on final scores and ranking in SAW analysis. Now we want to know how sensible is our ranking. In order to test the robustness of the ranking, we need to do sensitivity analysis. In three out of seven criteria the current policy has a better performance (see Table 12). We are interested to test the sensitivity of the current ranking if one increases the weights of these three criteria that the current policy has a better performance and decreases the weights of others.

By doing this experiment we can evaluate the effect of weights on final rankings. Thus we equally increase the weights of these three criteria (Min, Max, and Current Ideal/Baseline ideal) and equally reduce the weights of four other criteria (Reliability, 1-Vulnerability, Resilience, and Sustainability).

Table 14 shows the results of sensitivity analysis on the weights. The first row shows nine experiments. In experiments 2 to 9, the weights for the last three criteria, including minimum reservoir level, maximum reservoir level, and the ratio of the new ideal value for the reservoir to the ideal reservoir level in the Baseline are increased (see the second row of the Table 14). Simultaneously, the weights for the first four performance metrics, including Reliability, 1-Vulnerability, Resilience, and Sustainability are reduced (see the first row of Table 14).

In the first experiment, we assume that all seven criteria have the same weights and the weight of each criterion is equal to $1/7 = 0.143$ (see the first and second row of experiment 1). The third row of Table 14 shows the obtained scores using SAW analysis for the current policy. The fourth row displays the obtained scores using SAW analysis for the new policy. The last column demonstrates the difference between two policies scores. Having equal criteria weights, the score of the current policy is 0.887 and the score of the new policy is 0.973. The difference is equal to 0.087 and the new policy has a better overall performance.

In experiment 2, we assume that the weights for the first four performance metrics (Reliability, 1-Vulnerability, Resilience, and Sustainability) are equal to 0.125. We also assume that the weights for the last three performance metrics (Min, Max, and Current Ideal/Baseline ideal) are equal to 0.167. Basically, we systematically increase the weights of one group of criteria (the last three criteria) and decrease the weights of another group (the first four criteria). The magnitude of the reduction is equal to 0.013. As shown in Table 14, the current policy score for experiment 2 is equal to 0.776 while the new policy score is equal to 0.852 which is still higher.

The same procedure is followed and other experiments (3 to 9) are conducted. As illustrated in Table 14, enhancing the weights of the first four criteria increases the score of the current policy and decreases the score of the new policy. However, the current policy score is invariably below the new policy score. For instance, in experiment 9, even with such a great difference between the weights (0.283 vs 0.038) the new policy has a higher score (0.256) than the current one (0.233). Ergo, one concludes that the new policy is more robust compared with the current policy.

Table 14: The sensitivity analysis on the weights

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
The first four criteria weights	0.143	0.125	0.113	0.100	0.088	0.075	0.063	0.050	0.038
The last three criteria weights	0.143	0.167	0.183	0.200	0.217	0.233	0.250	0.267	0.283
Current policy score	0.887	0.776	0.698	0.621	0.543	0.465	0.388	0.310	0.233
New policy score	0.973	0.852	0.767	0.681	0.596	0.511	0.426	0.341	0.256
Difference between two policies	0.087	0.076	0.068	0.061	0.053	0.046	0.038	0.030	0.023

4.2 Conclusion

Water resource systems planning problems invariably involve uncertainties. Therefore, the aim of this chapter is to employ RDM for water resource system planning at river basins under deep uncertainty. We identify a set of performance metrics to analyze a river basin water resource system performance under evaporation/precipitation uncertainty. We also propose a combination of RDM and MADM to deal with uncertainty and select the most suitable strategy. MADM approach is helpful owing to their capability on being used as a decision making tool when decision makers need to evaluate and select a decision from a set of decisions considering different criteria.

In this chapter, the same water resource system as in Chapter 3 is used for conducting the experiments. More precisely, we analyze the system performance under evaporation/precipitation uncertainty using RDM. We generate future ranges for evaporation/precipitation of the reservoir coefficients. Then, we randomly sample from the range applying Monte-Carlo simulation. Four performance metrics are chosen from the literature. We evaluate the system under the current policy. Next, we suggest a new policy based on shifting the ideal rule curve of the reservoir and run the same samples to test the system performance. In order to be able to compare two strategies we use one of the MADM methods called SAW. Based on the SAW analysis the second strategy has a better overall performance. To test the robustness of the SAW ranking, we conduct a sensitivity analysis in MADM via changing criteria weights and assess the ranking. The sensitivity analysis results indicate that the suggested strategy is robust.

Further work includes adding adding uncertainty to more problem parameters, such as inflows and demands uncertainties into the model and analyze the combined effects. Another possible further research direction is increasing the number of samples or using other sampling methods. Furthermore, applying this model in a real river basin water resource system which is bigger and more complex is suggested.

Chapter 5

Robust optimization water resource planning model

In this chapter, we develop a robust water resource planning model for managing a water system under uncertainty in demand. Cardinality-constrained robust optimization is the main methodology we employ. To develop the robust model, we define the uncertainty set, budget of uncertainty, protection function, and its dual counterpart. Then, we design a set of experiments for a water resource system to test the robust model. Next, the results are summarized and a detailed discussion is provided. We show that the robust model can protect the decision maker against uncertainty in water resource planning problem at river basins. Using the model, the decision maker is able to make a trade-off between the cost of robustness and the feasibility of the solution.

5.1 A basin-scale water resource planning model under uncertainty

River basin water resource system management problems are generally subject to different kinds of uncertainties. Some of the factors that can cause uncertainty are: insufficient data, low quality data, inaccurate model, randomness of natural phenomena, and operational variability. The focus of uncertainty in this study is on uncertainty in model parameters.

5.1.1 Robust counterpart of the problem

The water resource planning model at river basin is affected by four uncertain parameters, namely random gain/loss coefficient of arcs (represent precipitation/evaporation), demands, inflows, and costs. In the model, these uncertain parameters are located in the coefficients, right-hand-sides, and objective function coefficients. To create the robust counterpart of the model, two steps need to be followed: (1) Formulate the protection function which is an optimization problem for the constraints that are affected by uncertain parameters. (2) Create the dual of the above-mentioned protection function for each required constraint and incorporate it into the model. The following section will explain the robust counterpart of uncertain constraints featuring the right-hand-sides uncertainty.

Uncertainty set Uncertainty set is an essential input for robust optimization problems. The uncertainty set is a set that contains values for the uncertain parameters. The set can have either finite or infinite cardinality. There are different ways of defining uncertainty sets (i.e., box uncertainty, ellipsoidal uncertainty, etc.); in this thesis, the uncertainty sets are defined as box uncertainty used by Bertsimas and Sim [20].

For each demand at node n in time t there is one demand arc associated with it. The maximum capacity of the demand arc in time t for node n is equal to the identified demand. Each uncertain item is modeled as a symmetric and bounded variable. In this thesis, we consider demand as an uncertain parameter in the model. Let's define $D\tilde{E}M_n^t$ as an uncertain demand parameter with the nominal value of $D\bar{E}M_n^t$ and the deviation value of $D\hat{E}M_n^t$. It is also time-dependent taking values in the interval $[D\bar{E}M_n^t - D\hat{E}M_n^t,\ D\bar{E}M_n^t + D\hat{E}M_n^t]$. Next, the new random variable $z_n^t = (D\tilde{E}M_n^t - D\bar{E}M_n^t)/D\hat{E}M_n^t$ associated with the uncertain parameter $D\tilde{E}M_n^t$ is defined, which follows an unknown but symmetric distribution, and its values belong to the range $[-1, 1]$. Ergo, it is possible to write $D\tilde{E}M_n^t = D\bar{E}M_n^t + D\hat{E}M_n^t z_n^t$. As it is demonstrated in Section 2.3.2, to create the robust counterpart of the model (7)-(14), the subsequent two steps are required. First, the protection function should be formulated as an optimization problem only for the constraints influenced by uncertain parameters. Second, having incorporated the dual of the protection function into the constraints, their robust counterpart will be created.

Budget of Uncertainty

Constraint (13) in the model imposes the demand for every node n in every time period t. In the current river basin water resource system only one node, which is a reservoir, has demand (see Figure 12). Each constraint that belongs into this block is subject to uncertainty, due to the fact that $D\tilde{E}M_n^t$ is an uncertain parameter. The uncertainty in $D\tilde{E}M_n^t$ can happen in any time period. Based on this assumption we cannot precisely predict which time period will be affected by uncertainty. In order to be able to use *"The price of robustness"* approach [20] and model right-hand-sides uncertainty, one needs to define a new decision variable for each uncertain right-hand-side parameter. The new decision variable should have the upper and lower bounds equal to one and it also should be multiplied to its associated uncertain variable. Next, we define a parameter Γ_{nt}, called the *budget of uncertainty* of constraint n in time period t. It can be either a fraction or an integer; and take values in the range $[0, |J_{nt}|]$, where J_{nt} is the set of all coefficients in constraint n in time period t that are subject to uncertainty. An integer value of this parameter can be interpreted as the maximum number of parameters that are possible to deviate from their nominal values [21]. Finally, S_{nt} is a subset of J_{nt} and $|S_{nt}| = \lfloor J_{nt} \rfloor$.

Protection function of Constraint (13)

The constraint that is subject to uncertainty is the demand constraint and the demand parameter, which is located in the right-hand side is uncertain. Thus, we rewrite constraint (13) as (16) below:

$$x_a^t \leq D\tilde{E}M_n^t \qquad \forall t \in \mathcal{T}, \forall n \in N, \forall a \in D_n \quad (16)$$

Let's define a decision variable, which we know will be assigned the value 1, $h_n^t = 1$ for each uncertain parameter $D\tilde{E}M_n^t$ and multiply them. Then, we have (17):

$$x_a^t \leq D\tilde{E}M_n^t h_n^t \qquad \forall t \in \mathcal{T}, \forall n \in N, \forall a \in D_n \quad (17)$$

Now, we can replace uncertain parameter with two parameters as follows:

$$x_a^t \leq (D\bar{E}M_n^t - D\hat{E}M_n^t) h_n^t \qquad \forall t \in \mathcal{T}, \forall n \in N, \forall a \in D_n \quad (18)$$

In order to show the general case we follow the standard procedure (for more information see Section 2.3.2 cardinality constrained robust optimization), however in our special case this procedure is not necessary because we only have one uncertain parameter. Additionally, in the general case there are more than one uncertain parameter in each row that should be selected among decision variables. So in the reformulated constraint the maximization function is responsible to select a number of decision variables from the range of decision variables up to a specific number in such a way that the function reaches its maximum value. Now, the reformulated constraint is suitable for creating the protection function. Incorporating the protection function into (13), we have (19):

$$x_a^t + \max\left\{\Gamma_{nt} D\hat{E}M_n^t h_n^t\right\} \leq D\bar{E}M_n^t h_n^t \qquad \forall t \in \mathcal{T}, \forall n \in N, \forall a \in D_n \tag{19}$$

In the general case as the maximization function also protects the decision maker against the worst-case it is called protection function. So the protection for node n and time t is (20). Following the general case, let's h_n^{*t} be the optimum solution of Formulation (19). Given a vector h_n^{*t} the protection function is (21):

$$\max\left\{\Gamma_{nt} D\hat{E}M_n^t h_n^t\right\} \leq D\bar{E}M_n^t h_n^t \tag{20}$$

$$\beta_{nt}(h_n^{*t}, \Gamma_{nt}) = \max\left\{\Gamma_{nt} D\hat{E}M_n^t |h_n^{*t}|\right\} \tag{21}$$

Linear equivalent of the protection function for Constraint (13)

Then, we have an equivalent of protection function. In the general case this function is still non-linear but in our case it is not true due to having one uncertain parameter in each row of the selected constraints. Thus, in order to proceed with the general approach we have:

$$\beta_{nt}(h_n^{*t}, \Gamma_{nt}) = \text{maximize} \qquad D\hat{E}M_n^t |h_n^{*t}| d_n^t \tag{22}$$

$$\text{s.t.} \qquad d_n^t \leq \Gamma_{nt} \qquad \forall t \in \mathcal{T}, \forall n \in N, \tag{23}$$

$$0 \leq d_n^t \leq 1 \qquad \forall t \in \mathcal{T}, \forall n \in N. \tag{24}$$

As in the general case the obtained optimization problem is not linear and in order to maintain the generality of presentation of the robust approach we proceed with the general approach. Using duality theory, we have that $\beta_{nt}(h_n^{*t}, \Gamma_{nt})$ is equal to the objective function value of the following problem (25)-(28).

$$
\begin{aligned}
\text{minimize} \quad & p_n^t + \Gamma_{nt} w_{nt} && && (25)\\
\text{s.t.} \quad & p_n^t + w_{nt} \geq D\hat{E}M_n^t |h_n^{*t}| && \forall t \in \mathcal{T}, \forall n \in N, && (26)\\
& p_n^t \geq 0 && \forall t \in \mathcal{T}, \forall n \in N, && (27)\\
& w_{nt} \geq 0 && \forall t \in \mathcal{T}, \forall n \in N. && (28)
\end{aligned}
$$

Substituting (25) to constraint (13) and adding (26)-(28) to the original problem, we obtain the linear robust formulation of the model, which is equivalent to the following linear problem:

$$
\begin{aligned}
\text{Minimize} \quad & \sum_{t \in \mathcal{T}} \sum_{a \in A \setminus \{\underset{n \in N}{\cup} D_n\}} c_a^t x_a^t + \sum_{t \in \mathcal{T}} \sum_{a \in \{\underset{n \in N}{\cup} D_n\}} c_a^t (u_a^t - x_a^t) && && (29)\\
\text{s.t.} \quad & \sum_{a \in H_n} g_a^t x_a^t - \sum_{a \in T_n} x_a^t = 0 && \forall t \in \mathcal{T}, \forall n \in N \setminus SSN, && (30)\\
& \sum_{a \in H_n} x_a^t - \sum_{a \in T_n} x_a^t = r^t && \forall t \in \mathcal{T}, \forall n \in SSN, && (31)\\
& \sum_{a \in H_n \cap O_n} g_a^t x_a^t - \sum_{a \in T_n \cap O_n} x_a^t = x_{a \in B_n}^{t+1} && \forall t \in \mathcal{T} \setminus \{P\}, \forall n \in N_1, && (32)\\
& x_a^1 = INS_n^1 && \forall n \in N_1, \forall a \in B_n, && (33)\\
& x_a^t = INF_n^t && \forall t \in \mathcal{T}, \forall n \in N, \forall a \in I_n, && (34)\\
& x_a^t + p_n^t + \Gamma_{nt} w_{nt} \leq D\bar{E}M_n^t h_n^t && \forall t \in \mathcal{T}, \forall n \in N, \forall a \in D_n, && (35)\\
& 0 \leq l_a^t \leq x_a^t \leq u_a^t && \forall t \in \mathcal{T}, \forall a \in A, && (36)\\
& h_n^t = 1, && \forall t \in \mathcal{T}, \forall n \in N, && (37)\\
& p_n^t + w_{nt} \geq D\hat{E}M_n^t h_n^t && \forall t \in \mathcal{T}, \forall n \in N, && (38)\\
& y_n^t \geq 0 && \forall t \in \mathcal{T}, \forall n \in N && (39)\\
& -y_n^t \leq h_n^t \leq y_n^t && \forall t \in \mathcal{T}, \forall n \in N, && (40)\\
& w_{nt} \geq 0 && \forall t \in \mathcal{T}, \forall n \in N, && (41)
\end{aligned}
$$

Now in our case we can replace h_n^t with 1.

5.2 Experimental results for the robust model

The water resource system presented in Figure 11 was used to test the proposed robust model. The input data for conducting a set of experiments was taken from the first experiment (also called the Baseline, for more details see Section 3.3.2 EXP1). We assume that the planning horizon ($|\mathcal{T}|$) is 12 months. The information about inflows and precipitation/evaporation coefficients, and costs are known. Expected demands for the next 12 months (one year) are uncertain.

To carry out the experiments, we define a number of test problems that are identifiable by the level of variability of the uncertain parameter represented by γ and budget of uncertainty represented by Γ. Both variations and budget numbers are in percentages. More precisely, we define γ as the level of variability of demand compared to its nominal value. It can vary between $\gamma = 0\%$ (no variability) to $\gamma = 100\%$ (maximum variability). So the relationship amongst the deviation, variability, and nominal data is shown by the equation $D\hat{E}M_n^t = \gamma D\bar{E}M_n^t$. Whilst setting the budget of uncertainty Γ for demand constraints, we define $\Gamma = 0\%$ (optimistic) to $\Gamma = 100\%$ (pessimistic), but still reasonable for the applications of interest.

Lastly, in order to test the quality of the robust optimal solution (in terms of feasibility or probability of constraint violation) Monte-Carlo simulation is implemented to generate random scenarios for uncertain demand parameter from its corresponding uniform distribution. For all generated scenarios, the optimal solution of the robust model is entered into the deterministic model and the uncertain parameters of the deterministic model are replaced by the simulated values. By doing so, both the feasibility and the actual objective function value of the robust solution are verified.

The robust model in this thesis is coded in OPL and solved using CPLEX 12.7, on a PC with 3.50 GHz CPU and 16.00 GB of RAM. The time to solve the robust problems to optimality range from 2 to 2.5 seconds which is 25% more than the deterministic model, but still reasonable for the applications of interest.

5.2.1 Design of experiments and results

In this section a set of experiments with different variability levels and budgets of uncertainty are designed to demonstrate the behavior of the robust model. In this study, the uncertain parameter is demand and we define four test problems with four levels of variability, $5\%, 10\%, 15\%$, and 20%. We also consider six budgets of uncertainty in our test problems contains $0\%, 5\%, 25\%, 50\%, 75\%$, and 100%. The greater the budget of uncertainty, the more conservative one is.

Our experiments have three goals. The first goal is to examine the trade-off between the level of variability and the budget of uncertainty considering the objective function cost. This evaluation shows the price of robustness. Applying this analysis, the decision maker is able to set the budget of uncertainty that is not too costly.

The second aim is to assess the effect of different budgets of uncertainty on the feasibility of the obtained solutions. This is an important factor due to the fact that increasing the budget of uncertainty leads to improving the feasibility of the obtained robust solution but also increases the objective value cost. Therefore, the decision maker has to set a favorable budget of uncertainty taking into account the future uncertainties at a reasonable cost. To verify the feasibility of the robust plan considering the uncertainties Monte-Carlo simulation is used. Monte-Carlo simulation systematically generates samples from a distribution of the uncertain parameter. Samples represent future scenarios and are employed for assessing the impact of the budget of uncertainty on the feasibility of the robust solution considering the objective function cost.

The third goal is to compare the objective function value of the robust model and the objective value function of the deterministic model for the worst-case scenario in order to identify the conservatism degree. It is a measure to assess how costly the obtained robust solution. A conservative solution is called over protected against uncertainty when it is overly costly.

Experiment 1. The trade-off between the cost of robustness and the budget of uncertainty

As it was mentioned earlier, the first experiment demonstrates the performance of the robust model under different budgets of uncertainty and levels of variability. The uncertain demand affects the water resource planning and it causes variations for water level in the reservoir. It is worth mentioning that the demand constraint (13) is defined as a less than equality constraint, on account of providing freedom for the model to decide the allocation trade-off between the demand and the reservoir considering their costs. This constraint controls the maximum amount of allocated water to the demand and can be seen as a capacity constraint. Going beyond this capacity the system will be infeasible owing to lack of having a tank/reservoir for keeping extra amount of water for the demand.

Figure 27 depicts the water resource system allocation cost for test problems. Total cost variable (on the y-axis) shows the amount of objective function value of four test problems under different budgets of uncertainty. The x-axis represents budget of uncertainty that varies from 0% to 100%. As seen in Figure 27, all the test problems converge on the same objective function value when the budget of uncertainty is equal to zero (no uncertainty). It is an optimistic perspective which is the same as the deterministic case and has the lowest cost compared to other robust models. When uncertainty is enforced to the robust model, the objective function value is growing. The more robustness is imposed, the less the objective value function will be. In such cases, the magnitude of allocated water to demands decreases which cause the water level in the reservoir to increase, also leading to an increased risk of flood in the system. The pessimistic perspective, which is the Sosyter model (100% budget of uncertainty), has the highest total cost amongst other budgets of uncertainty. Furthermore, one can infer from the Figure 27 that the impact of the budget of uncertainty on the objective function value is greater than the level of variability for high variability levels (i.e., 15% and 20%). Whilst for the low levels of variability (e.g., 5%), effect of imposing robustness on the objective function value by variability is more significant than the budget of uncertainty.

Figure 28 shows the percentage increase in the objective function value of all test problems under different budgets of uncertainty comparing to their nominal ones (no variability and no uncertainty). As shown in Figure 28, enforcing the robustness causes increasing the value of the objective function. Therefore, it indicates that as the budget of uncertainty increases, a greater number of uncertain parameters take their worst-case values. Consequently, this leads to increased water level in the reservoir and to an increased risk of flood.

Experiment 2. The trade-off between the budget of uncertainty and probability of constraint violation

The second experiment illustrates the behavior of the robust model based on its performance regarding the feasibility of the solution in the presence of uncertainty. In

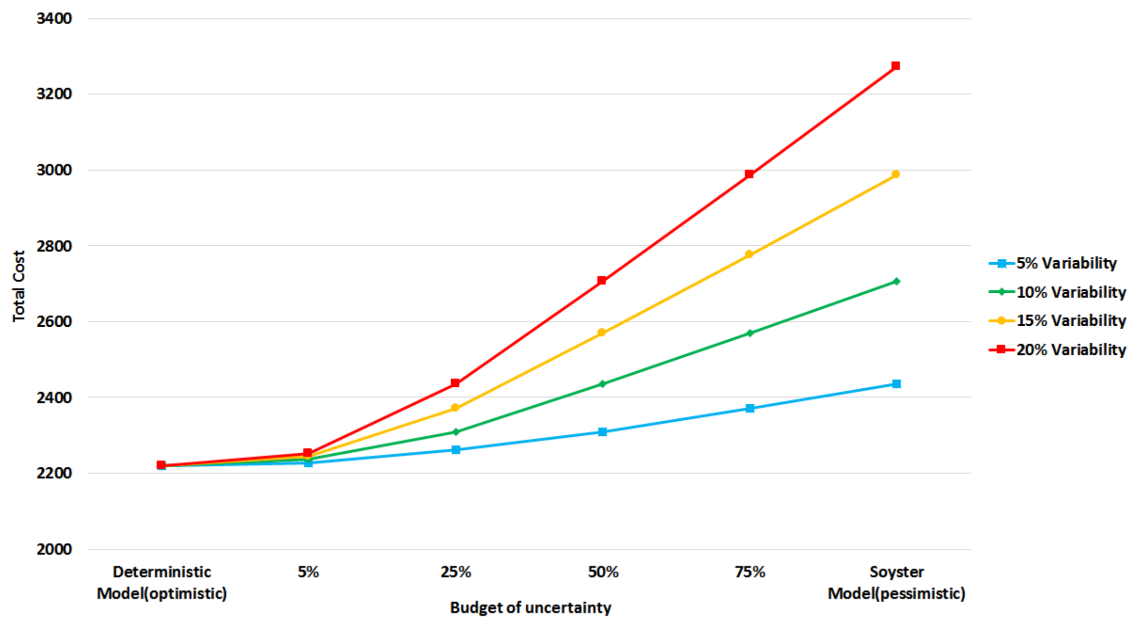

Figure 27: The trade-off between the budget of uncertainty and the objective function value in the robust model

robust optimization problems, two essential questions arise: what level of uncertainty should be accepted by decision makers and how much feasible the solution needs to be remain in the presence of uncertainty. The feasibility of a solution is calculated by constraint violation probability under uncertainty. When the system cannot be remain feasible under uncertainty; this impacts on the reliability of the system. Therefore, feasibility can be regarded as reliability. In addition, the two mentioned questions are conflicting because more uncertainty decrease the reliability.

As conservatism raises, constraint violation probability (infeasibility) decreases. In the budgeted uncertainty model, originated by Bertsimas and Sim [20] degree of conservatism, Γ, governs the feasibility of the results (see Section 2.3). In order to analyze different budgets of uncertainty (below the maximum budget) in terms of their feasibility Monte-Carlo simulation is employed.

Using the simulation and testing different budgets of uncertainty, one can choose an acceptable budget of uncertainty more reasonably. Ergo, we randomly generate 100 demand values for each level of variability and also for each value of budget of uncertainty. As a result, in order to examine the feasibility and the level of uncertainty of the robust solution, $100 \times 4 \times 5 = 2,000$ deterministic models are solved.

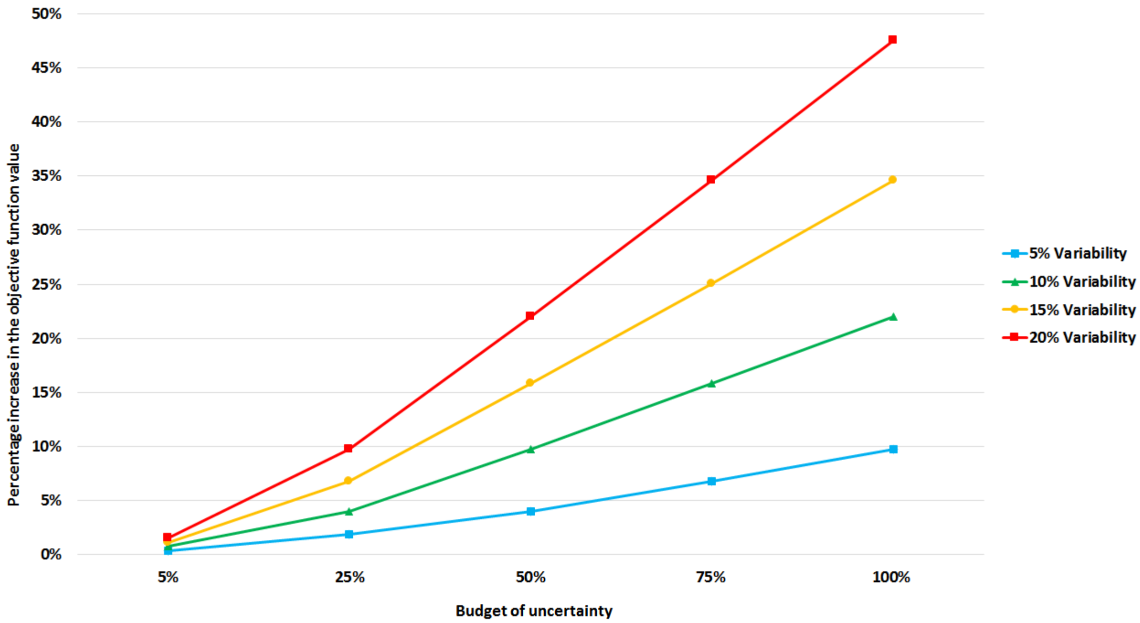

Figure 28: The trade-off between the budget of uncertainty and change in the objective function value compared the nominal

More precisely, we solve the deterministic water resource planning model for each scenario, where the planning extracted from the robust model is plugged into the above-mentioned deterministic model. Following this process, we analyze the feasibility of the obtained robust solution in the deterministic problem using simulated random demand samples. Figure 29 depicts the results for four classes of test problems. As illustrated in Figure 29, when the budget of unceriaty is greater than 75% the number of infeasible instances are equal to zero. Therefore, a decision maker can consider $\Gamma \geq 75\%$ to guarantee the feasibility of solutions for random parameter. Thus there is no need to increase the value of Γ and impose more cost. For the two test problems with less variability (i.e., 5% and 10%) a decision maker can select $\Gamma \geq 50\%$ if he/she is less conservative.

Experiment 3. In this experiment, we compare between the robust solution with 100% budget of uncertainty and the worst-case (WC) deterministic problem. In this comparison, Z^{WC} represents the objective function value obtained from the deterministic model for the worst-case scenario and Z^{R} represents the objective function value

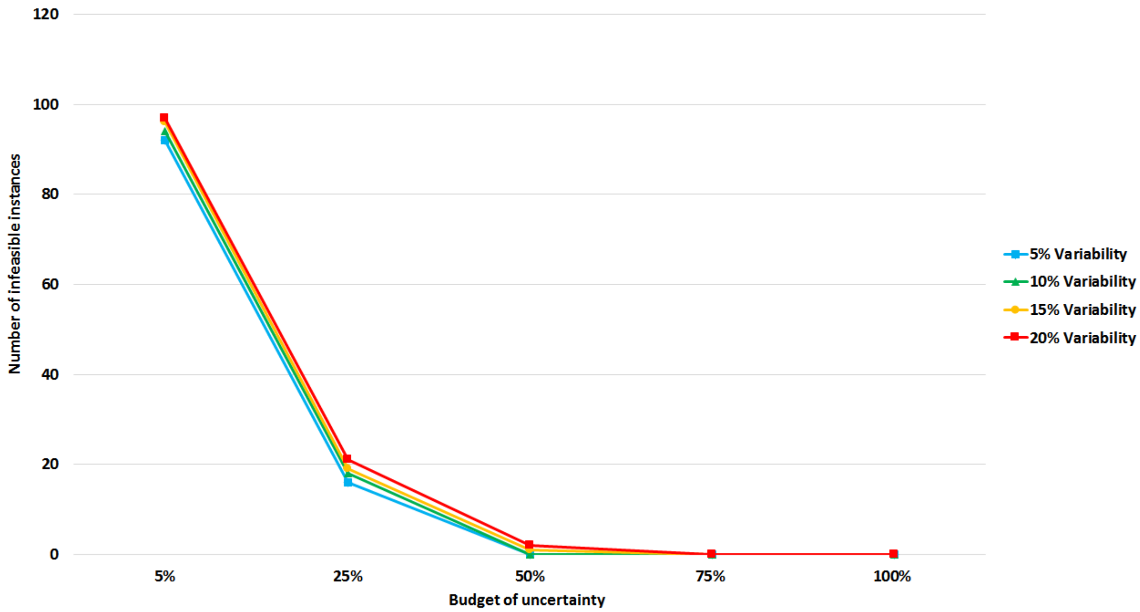

Figure 29: The trade-off between the budget of uncertainty and feasibility of robust solutions

acquired applying the robust model. In minimization problems, if $(Z^{WC} - Z^R) \geq 0$, one concludes that the robust model provides a solution withe lower cost [157]. Table 15 presents the comparison between Z^{WC} and Z^R of all variability levels. As $(Z^{WC} - Z^R) \geq 0$ for four variability levels, one concludes that the robust problem performs the same as the worst-case scenario solution obtained by the deterministic model. In general, in bigger problems and more uncertain parameters, we expect to see a difference in favor of robust model.

Table 15: Comparison analysis of the robust model with the worst-case scenario

	γ=5%	γ=10%	γ=15%	γ=20%
Z^{WC}	2436	2707	2987	3273
Z^R	2436	2707	2987	3273

5.3 Discussions

The purpose of this chapter is to develop the robust water resource planning model using the deterministic model based on the methodology called cardinality-constraint robust optimization. We use budgeted uncertainty which is a more realistic way to deal with uncertainty. The model is affected by four uncertain parameters and we are interested in demand uncertainty which locates in the right-hand-side of the model. Using a set of test experiments, we investigate the effect of the uncertain parameter on the obtained results. More precisely, we design for test problems with four different variability levels and we also consider several uncertainty budgets.

Our results indicate that the uncertain parameter has an impact on the water allocation planning. When the uncertainty is imposed to the model the magnitude of the allocated water to the reservoir rises. This poses flood risk, which is the worst thing that can happen in the system, owing to the limited capacity of the reservoir to store water. Flooding is more hazardous than not fully meeting demands. Moreover, as the budget of uncertainty or variability level increases, the objective function value becomes worst (here it grows). In addition, the impact of the budget of uncertainty on the objective function value is greater than the level of variability for high variability levels, but, for the low variability levels it is the opposite. Additionally, considering $\Gamma \geq 75\%$ guarantees the feasibility of the solutions for the random parameter. Furthermore, the robust problem outperforms the worst-case scenario solution obtained by the deterministic model. Thus the robust solution protects the decision maker in the presence of uncertainty.

In the illustrative example, there is only one demand arc and the trade-off is between the reservoir and the demand. In other cases, when there are more number of demands or reservoirs the situation is more complex. Furthermore, if there is relationship amongst demands (i.e., $2D_1 \geq D_2$) finding the worst-case will be much more harder but it provides greater number of inequality constraints which is suitable for using robust optimization.

5.4 Conclusion

Water resource systems planning models are subject to uncertainty owing to climate change, population dynamics, land use change, etc. Robust optimization is a subfield of operations research that seeks to find an optimum solution in the presence of uncertainty. In this chapter, we develop a basin-scale robust water resource planning model using cardinality-constrained approach to address demand uncertainty.

We conduct a set of experiments to demonstrate the trade-off between the level of robustness and the cost of robustness. We also use Monte-Carlo simulation to analyze the performance of the model in terms of its feasibility in the presence of uncertainty. The obtained results show the high quality of robust solutions considering feasibility and cost. The aforementioned results aid the decision maker to opt the right budget of uncertainty in such a way that the feasible plan under uncertainty is found.

Further research would focus on implementing the model on a real system which is bigger and more complex. In addition, using robust optimization under correlated data is recommended.

Chapter 6

Conclusions and future research directions

In this final chapter, we summarize the work presented in previous chapters, re-state the major contributions of this thesis and present some possible directions for future work.

6.1 Conclusions

Water is a precious resource and it is not uniformly spread in time and space. Additionally, water resource systems are under pressure owing to climate change, population growth, inept management, unsustainable use of water, and socio-economic developments. Therefore, water resource systems management is a salient task for all countries and one of the grand challenges humankind faces right now.

Water resource systems have been historically managed based on stationary assumptions in water supply and demand. However, these assumptions are routinely invalid in such systems owing to the difficult-to-predict changes affecting linked human-water systems [130]. Untrusted stationary assumptions combined with other sources of uncertainties lead to enhancing uncertainty levels in water resource systems. Ergo, there is a requirement to recognize these uncertainties and incorporate them in models for better management of such systems.

In this thesis we study the river basin water resource planning problem. In order to represent the identified priorities of the systems' components, multiple arcs are employed to create a piecewise linearized function of the costs/priorities. Then, the planning problem is mathematically formulated as a minimum cost network flow problem with multiple arcs. The deterministic model seeks to find the minimum cost allocation plan over a given planning horizon. We develop a deterministic model that optimally allocates water in the selected river basin.

To address uncertainties using the deterministic model, we first test the model performance under the effect of shift in the timing of the annual peak of flows and show that the model is vulnerable under both right and left shift. Second, we apply the RDM methodology to analyze the system performance under evaporation/precipitation uncertainty. Monte-Carlo simulation is used to take samples from the uncertain future ranges. The current policy is assessed and a new policy is suggested. MADM methodology is proposed for trade-off analysis phase in RDM as well. More precisely, the SAW methodology is employed for evaluation of the alternatives and ranking considering different criteria. To test the sensitivity of the robust strategy, the weights criteria are perturbed in SAW methodology. The sensitivity analysis indicates that the ranking is robust. We demonstrate that the combination of RDM and MADM is a suitable approach for dealing with deep uncertainty and selecting the most suitable robust strategy.

In the fifth chapter, we reformulate the above-mentioned deterministic model applying cardinality-constraint robust optimization approach to address uncertainties. The performance of the robust model under different budgets of uncertainty and levels of variability is analyzed. The feasibility of the solution in the presence of uncertainty is evaluated using simulations as well. This approach aids decision makers to identify an appropriate budget of uncertainty considering the trade-off between the allocation robustness and the cost of robustness. Using this methodology, water resource managers can optimally allocate water in the presence of uncertainty.

The major contributions of this thesis are as follows. First, we provide a clear procedure to mathematically model a river basin water resource allocation problem when there are competing demands and different operating priorities.

Second, we employ RDM when the future conditions are highly uncertain or there is not an agreement regarding future states of the system. MADM is also employed for evaluation of the alternatives using identified performance metrics in RDM methodology. The combination of RDM and MADM provides a systematic evaluation procedure for decision makers in process of selecting the most robust strategy.

Third, we use RO to address uncertainties when the future conditions are uncertain, but there is an agreement about the uncertainty sets. Cardinality constrained robust optimization methodology is employed for water resource planning problem. The model provides the option of controlling the level of robustness of the solution in terms of feasibility in the presence of uncertainty against the cost of such a robust solution for decision makers.

6.2 Future research directions

To extend the current direction of this thesis, we separately suggest future work for each chapter below.

For chapter three, further work includes incorporating other components of water river basins such as hydropower plants, apportionment channels, etc. into the mathematical model. Furthermore, future work should focus on using this approach to model a real water river basin and comparing our model to models in existing software.

In chapter four, future work includes adding uncertainty to more problem parameters, such as inflows and demands, into the deterministic model and analyzing the combined effects. Another possible further research direction is increasing the number of samples or using other sampling methods (i.e., Latin hypercube sampling). Furthermore, applying this model in a real river basin water resource system which is bigger and more complex is suggested. Using other MADM methods and comparing the results with the current ones is another interesting direction for future work.

In chapter five, further research would focus on implementing the model on a real system which is bigger and more complex. In addition, using robust optimization under correlated data is recommended. It would also be interesting to extend the current research using other uncertainty sets and comparing the results. In real problems, we might encounter uncertain travel times of flow [67] in networks. Thus, further study could apply RO in the presence of uncertain travel times of flow in the network.

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