Identifying urban drainage system adaptation measures through explorative modelling

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Abstract

The urban drainage system has become more and more vulnerable under the increasingly severe climate changes conditions and ecological problems over the past decades. New paradigms such as Sponge Cities and Water Sensitive Urban Design (WSUD) have emerged to supplement the urban flood-resistance capacity without massively retrofitting the underground system. Compared with the traditional urban infrastructure construction, water sensitive urban design is 1) more complex as decentralized facilities are susceptible to centralized systems, 2) aiming more at long-term multi-benefits of separate facilities that have very limited individual capacity and 3) vulnerable to future uncertainties such as land use changes. Currently, none of the existing methods can comprehensively consider the long-term adaptation of the complex urban water system (centralized + decentralized), which not only needs to cover the overall design of various independent systems, but also evaluate the integrated performance of the system under the uncertainty of the future.

The purpose of this thesis is to develop a planning method that provides step-by-step and time-dependent urban water infrastructure implementation pathways, which covers a range of water systems and various uncertain factors in the future, while improving the sustainability and liveability of urban water system and even the whole city.

Three different case studies were selected considering their compatibility to different research tasks. A rural catchment (with very a small centralized system) was used to ensure accurate and differentiated analysis for decentralized system planning where as a larger and urbanized catchment was studied for more adequate information for the centralized network system (e.g. topology structure of the network). A smaller catchment with balanced amount of centralized and decentralized system was adopted for testing the methodology in explorative modellings (to reduce the overall runtime).

The first research phase proposed a planning method which integrates a GIS fuzzy process and hierarchical fuzzy inference system for urban flood

vulnerability assessment and WSUD planning. The method was tested in Yangchen Lake Peninsula, China. The application showed that the method could maintain the dominant characteristics of the designing elements while taking into account the surrounding environment and revealing hidden information with limited data availability. By analysing the flood resistance capacity from the WSUD plan through this method, a drainage network expansion algorithm was developed for simulating the feedbacks between WSUD plans and network plans. The algorithm was tested in the Elster Catchment in Melbourne and replicated similar topological structure compared to the real one while having far less vulnerable junctions.

After establishing the feedback between infrastructure plans (WSUD and drainage network), a three-stage model was designed to explore possible futures of urban water infrastructure plans, identify the robust infrastructure scenarios against future flooding and optimize the adaptation plans. The model was tested in Scotchman's Creek in Melbourne and was capable of generating urban water infrastructure implementation pathways with multiple infrastructure options to achieve multiple objectives.

Lastly, two acceleration modules were designed based on artificial neural network (ANN) and rough set theory (RST) to reduce the simulation time of the global exploration stage and increase the applicability of the three-stage model. The acceleration module, designed with ANN, can reduce the total simulation time by 80% while maintaining its prediction accuracy. An error correction method based on the validation process has also been proposed and tested to solve the overestimation of this module. The acceleration module based on rough set theory is capable of dynamically adjusting the exploration speed (timesaving: 16.45% - 82.47%) and prediction accuracy (r: 0.9418 – 0.6963).

The three-stage pathway generation model was developed on the basis of two validated models (SWMM and DAnCE4Water), the result from the global exploration was used to validate and analyse the performance of the acceleration module. The research results in this thesis provide important insights and models for improving the robustness of long-term urban water infrastructure to support the uptake of sponge cities.

Thesis including published works declaration

I hereby declare that this thesis contains no material which has been accepted for the award of any other degree or diploma at any university or equivalent institution and that, to the best of my knowledge and belief, this thesis contains no material previously published or written by another person, except where due reference is made in the text of the thesis.

This thesis includes two original papers published in a peer-reviewed journal (Chapter 3, Chapter 5 and 7). The core theme of the thesis is to develop a planning method that ensures the highly invested sponge infrastructure implementation plans can meet the needs of future cities during and after its transition. The ideas, development and writing up of all the papers in the thesis were the principal responsibility of myself, the student under the supervision of Dr Christian Urich (Monash University) and Professor Dafang Fu (Southeast University).

For Chapter 3, the contribution of the co-authors can be described as follows: Dafang Fu: research formulation; Yajun Wang: data analysis; R.P. Singh: editing. For Chapter 4, the contribution of the co-authors can be described as follows: Dafang Fu: research formulation; Christian Urich: research formulation. For Chapter 5, the contribution of the co-authors can be described as follows: Dafang Fu: research formulation; Ana Deletic: research formulation; Christian Urich: research formulation. For Chapter 6, the contribution of the co-authors can be described as follows: Dafang Fu: research formulation; Christian Urich: research formulation; R.P. Singh: editing. For Chapter 7, the contribution of the co-authors can be described as follows: Dafang Fu: research formulation; Ana Deletic: research formulation; Christian Urich: research formulation.

In case of the two published papers, my contribution to the work involved the following:

Thesis Chapter	Publication Title	Status	Nature and % of student contribution	Co-author name(s) Nature and % of Co-author's contribution*	Co-author(s), Monash student Y/N*
3	Detailed sponge city planning based on hierarchical fuzzy decision-making: A case study on Yangchen Lake	Published	75 %: research formulation, data collection, modelling, writing	1) Dafang FU: research formulation (5 %) 2) Yajun Wang: data analysis (5 %) 3) R.P. Singh: editing (5 %)	No
5 and 7	Accelerated Exploration for Long-Term Urban Water Infrastructure Planning through Machine Learning	Published	75 %: research formulation, data collection, modelling, writing	1) Dafang FU: research formulation (5 %) 2) Christian Urich: modelling (5 %) 3) R.P. Singh: editing (5 %)	No

I have/have not renumbered sections of submitted or published papers in order to generate a consistent presentation within the thesis.

Student signature: **Date:** 22/09/2020

The undersigned hereby certify that the above declaration correctly reflects the nature and extent of the student's and co-authors' contributions to this work. In instances where I am not the responsible author, I have consulted with the responsible author to agree on the respective contributions of the authors.

Main Supervisor signature: **Date:** 22/09/2020

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Content

Nomenclature

Acronyms / Abbreviations

AHP	Analytical Hierarchy Procedure
AM-ANN	Acceleration module based on artificial neural network
AM-RST	Acceleration module based on rough set theory
BAU	Business as usual
CR	Consistency ratio
HFDM	Hierarchical fuzzy decision making
HFIS	Hierarchical fuzzy inference system
MCDM	Multi-criteria decision making
PIPE	Upgrade the pipe system
RWHT	Rainwater harvesting tank
RST	Rough set theory
WSUD	Water sensitive urban design

Chapter 1.

Introduction

1.1 Overview

Urbanisation has changed the permeability of land which leads to more runoff in urban areas during rain events. To avoid flooding and subsequent damages to properties and impacts on human safety and health, surface water needs to be drained and removed in time. Historically, this has been achieved by using underground pipe systems designed to convey the water away as quickly as possible, or by using retention ponds designed to store as much water as possible.

Urban drainage systems are designed to serve for decades. However, their planning and design process considers only limited adaptability to future changes. Traditional urban drainage systems, which are usually planned for a lifespan of 50-100 years using designed rainfall, have therefore become more and more vulnerable to increased urbanisation and the increasing impact of climate change. The premature failure and poor adaptability of the current urban water infrastructures highlights the limitations of the traditional long-term planning processes of these systems.

New paradigms such as Sponge Cities and Water Sensitive Cities have emerged to supplement the urban flood-resistance capacity without massively retrofitting the underground system. Such concepts also aim at overcoming limitations of current urban water management and expanding environmental service to provide green and blue cites to restore the local climate. Compared with the traditional urban development, the contribution to flood mitigation from water sensitive design is smaller and more decentralized while the investment of which is larger and aiming more at long-term benefits.

Future urban scenarios such as master plans, population growth, and climate change can never be certainly predicted in the long-term. The most convincible case is the "shrinking city" phenomenon in Dresden, Germany. As the capital of the Saxony state, the second largest city in eastern Germany, experts believe the economy, population will get rapid development after the unification in 1990. Large-scale construction of infrastructures was carried out to serve the rapid development. But in a few years, Dresden’s population was shrinking rather than growing, its demand for water was sharply reduced, and the water system facilities that the government planned and invested in for a long time did not promote the city's development but became a drag. In order to minimize losses, Dresden predicted the future population trend for seven times in the following 15 years and revised the urban planning, but none of the predictions was correct (Moss, 2008; Wiechmann & Pallagst, 2012).

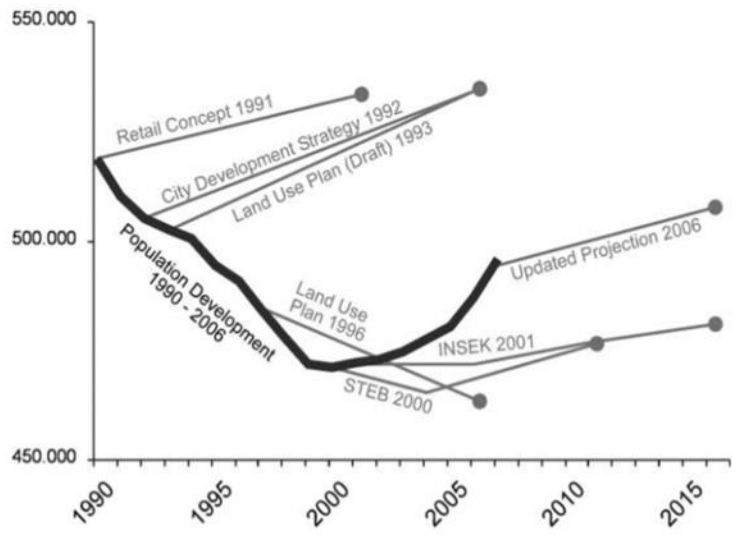

Figure 1.1 Projections and realities of population development in Dresden since 1990 (Wiechmann & Pallagst, 2012)

When dealing with future uncertainties, existing planning methods cannot provide adequate robustness or adaptability to alternative plans in the long term, as these “uncertainties” are often not statistical in nature(Walker, Haasnoot, & Kwakkel, 2013). For the urban water system, the uncertainty includes not only the state of the city (economy, climate, etc.), but also the human factors (population, etc.)(Lempert, 2003; Quade & Carter, 1989). Although some researchers have realized this problem and tried to "optimize" the system based on possible future scenarios, this static optimization process is often carried out with a limited number of future scenarios and cannot provide reliably high-adaptability plans(Walker et al., 2013). Therefore, the emerging planning methods are more inclined to provide different but interchangeable plans and implementation pathways.

Currently, none of the existing methods can comprehensively consider the long-term adaptation of complex urban water system, which not only needs to cover the overall design of various independent systems, but also to evaluate the collective performance of the system under the uncertainty of the future.

The aim of this thesis is therefore to develop a planning method to provide step-by-step and time-dependent urban water infrastructure implementation pathways, which covers all kinds of water facilities (structural and non-structural, traditional and new) and various uncertainty factors in the future, so as to improve the sustainability and reliability of urban water system and even the whole city.

1.2 Overall aim and tasks

The purpose of this thesis is to develop a new dynamic adaptive optimization planning method for urban water system planning which provides step-by-step construction guidance, covering the structural strategies of various facilities and non-structural policy measures, considering various uncertainty factors in the future, so as to improve the sustainability and reliability of the urban water system. The main research questions are as follows:

1. In the planning of green infrastructures, how to improve the decision reliability under limited data availability and reduce the uncertainty of planners' subjective perceptions?

2. In the planning of grey infrastructures, how to comprehensively consider the influence of green infrastructure planning in different construction stages and to improve the robustness of grey-green systems?

3. How to deduce the urban development and the construction of complex drainage system, while identifying problems in the long-term construction and operation process to generate a robust urban water implementation pathway?

4. How to improve the identification speed of urban water implementation pathway and improve the applicability of this method?

1.3 Scope of the research

This research aims to develop methods for identifying robust water infrastructure implementation pathways to increase the resilience to the changing demand of water service, across the exploratory space for futures under deep uncertainty. Although the aim is to develop a general method that can be applied to all urban water streams (supply, sewage and drainage), the work will in the first instance focus on adaptation of urban drainage system to assure a city's flood resilience.

1.4 Outline of the thesis

The thesis will consist of eight chapters. An overview of each chapter is provided below.

Chapter 1: Introduction

This chapter introduces the background and purpose of this study, overall research aim and objectives, scope of the research, and culminates in providing the outline of the thesis.

Chapter 2: Literature review

This chapter first defines infrastructure and typical infrastructure planning process to clarify the object and model framework of the research. The changing focuses of long-term infrastructure planning is then discussed to address the multiple objectives of infrastructure planning considered in this research. A review of popular methods, regarding both structural and non-structural infrastructure planning, used to fight against urban flooding issue is also provided to determine the candidate strategy options used in this research. Finally, a review of current methods which can be used to develop plans for infrastructure implementation, especially in water system, is carried out. This includes a review on tools focusing on the social influences and feedbacks, tools that aim at optimizing or modifying existing plans, and tools which try to build up adaptive and flexible plans through time. A conclusion summarising the literature and the research gaps is provided.

Chapter 3: Hierarchical fuzzy evaluation of spatial vulnerability and WSUD suitability in urban areas

In this chapter, we developed an easily applicable decision-making framework that applies a hierarchical FIS system (Şener & Şener, 2015) on a fuzzified GIS system, in order to offer better decision supports with fewer user-defined data.

The hierarchical FIS system aims to reduce the subjective judgement from planners, minimizing uncertainty in the system. The fuzzified GIS system provides comprehensive information on the surrounding environment to support better decisions. The developed framework and the traditional MCDM method were applied on a planning program at Yangchen Lake Resort, Suzhou, Jiangsu, China. The results of both methods were compared so that the pros and cons for each approach could be analyzed.

Chapter 4. WSUD-dependent drainage system design

In this chapter, a WSUD-dependent urban drainage planning method is proposed. On the basis of urban spatial vulnerability assessment method proposed in chapter 3, the planners could expend the existing network to more vulnerable areas and optimized the size and layout of the drainage system.

Chapter 5. Urban water infrastructure implementation pathway

In this chapter, an optimal plan and transition design method of water system through global scenario exploration is proposed to improve the adaptability and robustness of long-term urban water system planning. Starting from the current state of the city, all reasonable urban development situation at each time step (climate, population, economy, etc.) were explored as well as possible urban water system construction (construction of WSUD facilities, expansion pipe network, etc.). By evaluating the efficiency of water systems in all possible urban scenarios in a certain time step, the robustness of the system planning is analyzed, and the transition routes between schemes are designed.

Chapter 6. Acceleration of pathway exploration by deep learning

An acceleration module based on machine learning algorithm was developed to predict the performance of urban water system under different city scenarios and reduce exploration time. The following works have been conducted: (1) a comprehensive statistical trial-and-error analysis method is proposed and tested to avoid local optimization of network structure. (2) a neural network was integrated in the explorative adaptation planning to significantly reduce the simulation time, performance was tested and analyzed; (3) a correction method was proposed and tested to minimize the overestimation problem of the designed exploration framework.

Chapter 7. Acceleration of pathway exploration by dynamic learning

A dynamic accelerated global exploration module (AM - RST) is developed based on rough set theory in this chapter which, in the process of exploring, could continue to improve prediction accuracy by self-updating. The parameter "significance" is introduced, which changes the expression of causal rules in traditional rough theory. By expressing causal rules in a probability way, the influence of error distribution on decision-making is compensated, and the accuracy of (AM-RST) in practical application (especially when dealing with big data) is improved.

Chapter 8. Conclusions and future work

This chapter summarises the key findings in modelling and experiments. Conclusions and practical implications, and strengths and limitations of this study are highlighted. Recommendations for future work are also provided.

1.5 References

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Chapter 2.

Literature review

2.1 Introduction

This chapter aims to provide a critical review of the relevant literature which underpins the research questions outlined in this thesis. The literature review has been conducted to gain a better understanding of the knowledge which has already been gained in this field and to identify significant information gaps which this research aims to fill.

The chapter will begin by defining infrastructure and a brief overview of typical planning process to clarify the object of the research. The changing focuses of long-term infrastructure planning is then discussed to address the increasing demand (technical and social) of multi-function infrastructure. A review of popular methods, regarding both structural and non-structural infrastructure planning, used to fight against urban flooding issue is also provided.

Finally, a review of current methods which can be used to develop plans for infrastructure implementation, especially in water system, is carried out. This included a review on tools focusing on the social influences and feedbacks, tools that aim at optimizing or modifying existing plans, and tools which try to build up adaptive and flexible plans through time.

A conclusion summarising the literature that was reviewed and the research gaps that have been identified through this process have provided. These knowledge gaps have been used as the basis for the research questions within this thesis.

2.2 Overview

2.2.1 Long-term infrastructure planning

Infrastructure, as one of the fundamental parts of civilization has several definitions from different perspectives. (Jochimsen, 1966) first defined infrastructure as the important preconditions of economic development. It was regarded as the ensemble of material, institutional and personal facilities, and data that contribute to realizing the equalization of the remuneration of comparable inputs in the case of a suitable allocation of resources. Nevertheless, with the progress of urban development, attention gradually switched to the functionality of infrastructure. (Buhr, 2003) stated that each type of infrastructure should be defined according to its effects. He regarded infrastructure as the sum of all relevant economic data such as rules, stocks, and measure with the function of mobilising the economic potentialities of economic agents.

Technically, engineers limited the use of the term "infrastructure" to describe fixed assets in the form of networks. They regard infrastructure as the network of assets "where the system as a whole is intended to be maintained indefinitely at a specified standard of service by the continuing replacement and refurbishment of its components" (Group, 2000). With the rapid expansion of decentralized technologies, infrastructure now refers to facilities that usually require certain capital investments, provide “public services” and are planned, designed, constructed, and operated by or under the supervision of government agencies/private companies(Goodman, 2015).

The principal types of infrastructure include systems for transportation, water supply, wastewater, solid wastes, water resource management and electric power generation and supply. These systems are involved in the normal planning and budgeting processes of governmental and local public works agencies. They also constitute the principal elements of municipal engineering. Most of these facilities have generally recognized methods for estimating needs, and many may also be valued in terms of their tangible economic benefits (Goodman, 2015; Torrisi, 2009).

This research mainly focuses on the long-term planning of urban water infrastructures, especially flood-resistance systems. These systems are traditionally with long service life and built underground, which strongly requires adaptive and resilient planning.

2.2.2 Typical Infrastructure Planning Steps

Although more and more computational tools and methods have been developed to support infrastructure planning, they are more likely to be used for verification or evaluation rather than planning. In this section, the typical infrastructure planning process was investigated to support the framework design of a ‘planning’ model which could automatically and computationally replicate the manual planning process.

The methods of infrastructure planning range from simple approaches such as employing professional judgment to sophisticated computational optimization techniques. The selection of methods for a planning effort depends on the type of project, the requirement of planning organization, the available resources for investigations and the capabilities and preferences of the planning staff.(Goodman, 2015)

There are different planning protocols and guidelines for the different types of infrastructure at different places, however most infrastructure planning processes include the following steps.

1. Formulation of goals and objectives: setting up long-term plans and goals for the whole infrastructure system, considering broad policies and laws;

2. Problem identification and analysis—investigation and projection of relationships of demand and supply as well as investment, resource-consumption and profit; identification of risk and opportunities for development and management;

3. Solution development and impact assessment—design structural solutions and/or non-structural solutions to solve the problem, and assess the impacts;

4. Designing alternatives and analysis—comparison of different measures and detailed assessment of performance to optimized the design;

5. Recommendations—identifying priorities and setting schedules for implementation

6. Decisions—considering feasibility from technical, financial, legal and other aspect;

7. Implementation—confirming final design and construction planning, doing the construction;

8. Operation and Management—maintenance, renovation and retrofit.

In proceeding from the initial to the final phases of a planning and management process, the work in one phase can suggest changes in one or more of the other phases. This effect can be referred to as feedback, but the linkages may be in both forward and backward directions.

In this study, step 1 to 6 will be integrated into the proposed modelling framework and the linkages will be considered.

2.3 Objective of Long-term infrastructure planning

As discuss in 2.2.2, the objective setting is commonly the first step of infrastructure planning. The problem is complex when it comes to long-term infrastructure planning as the objective can change over time. A review of objectives was carried out in this section to identify possible goals of urban (water) infrastructures.

2.3.1 Provide social service

General economical implication

Infrastructure planning stabilizes the economy

When the term of long-range infrastructure planning first occurred in the 1920s (Mitchell, 1922), it was believed to provide increasing volume of construction work. In the UK, proposals for new parliamentary procedures for processing major infrastructure projects was raised in the early 19th century to promote enterprise and competitiveness and underpin the economy (Marshall, 2011). (Reid, 2008) mentioned a United States report, Infrastructure 2008: A Competitive Advantage, which suggests that regional and national infrastructure plans as well as government infrastructure management could keep competitiveness in the fluctuating global economy.

Economy constrain infrastructure planning

With the process of urban development, economic feasibility starts to become a critical factor in planning, especially in developing countries where infrastructure planning systems are complex, multi-levelled and underperformed relative to needs and expectations. (Romeo & Smoke, 2015) found that the 2008 global financial crisis affected resource availability for infrastructure and placed subnational governments in many developing countries under pressure of funding. The demand for more and better infrastructure increases with greater economic development, higher citizen awareness/expectations and the influence of external trends and global agreements (e.g. the Millennium Development Goals) after the crisis.

Infrastructure planning promotes the economy

Research also indicates that the viability of the economy is dependent upon a viable stock of public infrastructure. With commentators start highlighting the need for increasing spending on infrastructure, (Landers, 2014) found several report that seeks to highlight the economic benefits that the US would derive should such a boost in funding occur. Reports indicates that as a result of the added infrastructure spending, real GDP would increase in all major US industries, but construction and transportation would improve most.

Servicing a growing population

Serve daily use

One of the other principal function of infrastructure is to serve the need of a growing population. According to UN estimates 1.7 billion urban dwellers will be added to the urban population in the next 40 years(Duenas & Wegelin, 2011). Plans such as the Alexandra Renewal Project in 2001 was carried out to extend and renew infrastructure copping with a significant increase in population growth which has, and continues to, impact negatively on local infrastructure systems such as water (Landie, 2011). (Shepherd, 2005) analysed the population shift with the changing age profile and the resulting implications for infrastructure planning.

Offer work opportunities

After World War I, the closing down of war industries and the demobilizing of the army have produced an excess of labour. The water works superintendent is called upon to offer worth relief work in water infrastructures (Cuddeback, 1919). (Kurtzleben, 2011) found that infrastructure spending is more effective, dollar for dollar, than many forms of tax cuts at boosting jobs growth. (Leigh & Neill, 2011) examine the effect of a federally-funded local infrastructure spending program on local unemployment rates in Australia, which shows that higher government expenditure on roads substantially reduces local unemployment. Based on a statistical and spatialized analysis of unemployment in the Paris region, (L'Horty & Sari, 2013) found that the Great

Paris Express project could partially improve situation of working people in the Paris region.

2.3.2 Sustain future challenges

Sustainability

The concept of sustainability is to meet the needs of the present without compromising the ability of future generations to meet their own needs (Brundtland et al., 1987). The beginnings of the conversation in sustainability in the water sector are over the same period as the beginnings of the environmental movement in the 20th century when concerns were raised about the degradation of the environment by developments (Ho, 2010). The idea of sustainable design was carried out which has two objectives: to maximize the quality of the built environment and to minimize the negative impact to the natural environment (McLennan, 2004). (Sahely, Kennedy, & Adams, 2005) proposed a feedback mechanism in a framework that have important sustainability implications for both environmental and socio-economic aspects. The main goal of the infrastructure designer in a sustainable design is to provide the best service possible using the least amount of resources.

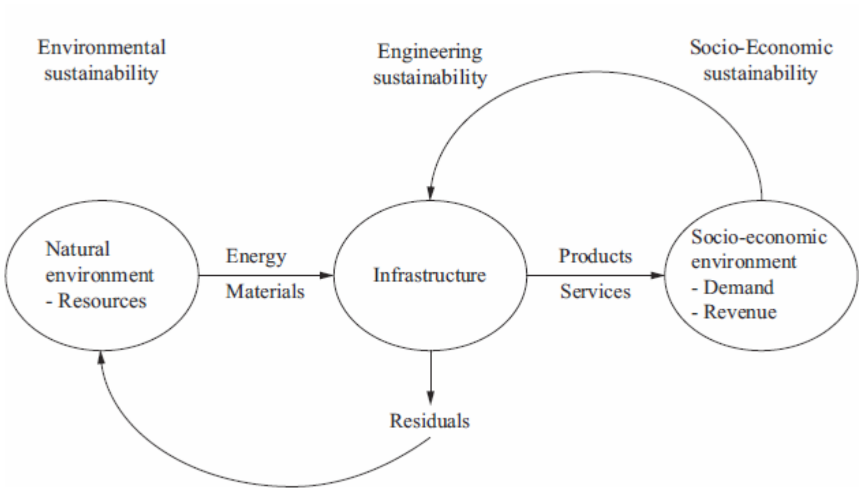

Figure 2.1 Framework for assessing infrastructure systems. (Sahely et al., 2005)

As a result, the design of infrastructure begins aiming at plan and manage resources while maintain their traditional functions (Goodman, 2015). For example, wastewater infrastructure for source separation is regarded as a promising concept while competitive technologies are being developed to overcome the inflexibility of the present end-of-pipe technology (Larsen, 2011); Feasible infrastructure plans are developed and compared by treating water with social value for seawater desalination systems (Fisher & Huber-Lee, 2011); Mathematical models are also developed to integrate and optimize urban water infrastructures for supply-side planning and policy (Lim, Suh, Kim, & Park, 2010).

Uncertainty

Urban water infrastructure is facing more and severer challenges in the process of urbanization. Cities are competing with each other as well as the environment to access enough quantity and quality of water resources. Meanwhile, climate change is generating more extreme weather events to aging infrastructures, increasing hydrological variability and higher uncertainty about water availability ("Water and Cities: Ensuring Sustainable Futures," 2015). These challenges are no longer contained within the traditional confines of water “issues” but are intertwined with energy, development, infrastructure, and overall issues of sustainability (Weinstein & Clifton, 2012).

Infrastructure planning is now coming across with problems that characterized by uncertainties: those resulting from a lack of information and those resulting from uncertainties about the future. The former one (lack of information) can generally be represented by probability distributions (Beh, Maier, & Dandy, 2015) while the latter one (unknow future) are often about the state of the world in the future (e.g. economic situation) and human factors (e.g. population growth) that impact on infrastructure functioning for which have no probability distributions, which is defined as ‘deep uncertainties’ (Robert J Lempert, 2003; Quade & Carter, 1989)

Although some planners are aware of the importance of such external factors, most of them still try to develop statistic “optimal” plans using single “most likely” futures based on extrapolation trends or a small number of hypothesized outlooks, these plans may be vulnerable to failure if deeply uncertain future conditions deviate from those assumed during optimization(Haasnoot, Kwakkel, Walker, & ter Maat, 2013; Herman, Zeff, Reed, & Characklis, 2014)

Considering the risks posed by these challenges, the term “robustness” has gradually been recommended in infrastructure planning. The concept of it is described as ‘the insensitivity of a system design to errors, random or otherwise, in the estimate of those parameters affecting design choice’ (Matalas & Fiering, 1977). According to Matalas, robust decisions should be adaptable to a range of “wait and see” strategies “with some economic efficiency or optimality traded in favour of adaptability and robustness”. (Mortazavi-Naeini et al., 2015) suggest that the selection of an approach to making robust decisions that is well suited to the problem context and the preferences of the decision maker is an important consideration.

In this research, the major objectives for urban water infrastructure (especially drainage systems) would be 1) daily use function such as performance on flood resistance; 2) economic function such as cost-efficiency; 3) sustainability and uncertainty such as adaptation capacity and routes over time.

2.4 Strategy options for water infrastructure planning against flooding

A review on typical urban water drainage infrastructures (options) for planning that can achieve the select objectives was conducted in this section.

2.4.1 Drainage network upgrade

As a result of increased urbanization, decreased infiltration rates, and climate change, flooding in cities has become one of the most significant problems. Aging urban drainage systems as well as their performances are prone to symptomatic decay under these situations. Physical measures aimed at reducing flood risks in a catchment scale, includes the development of local and regional water retention areas or canal broadening (Neuvel & Van Der knaap, 2010). Hydraulic rehabilitation plans can also be developed and implemented to maintain suitable urban drainage system performance against flooding (Sebti, Bennis, & Fuamba, 2013; Yazdi, Lee, & Kim, 2014).

2.4.2 Water Sensitive Urban Design

Water sensitive urban design (WSUD) denotes another approach to the planning and design of urban development, namely the integration of urban water systems with the natural water systems as part of the hydrological cycle

(Barton & Argue, 2007). To deal with flooding problems, possible application of WSUD includes swales, bioretention systems, rainwater tanks and etc. (AWA, 2005).

Unlike the drainage network which is designed for general urban services, WSUD focusses on smaller rain events rather than the exceedance events (B Gersonius et al., 2012). It also helps to achieve water conservation, control urban soil erosion and groundwater depression cone, reduce water pollution and improve the urban ecological environment goals (Che, Zhang, Li, Li, & Wang, 2010; Li, Wang, & Che, 2010)

2.4.3 Land-use planning

Land-use planning, also named as “zoning regulation”, limits the construction of buildings and development in certain flood plain, hence reduces its vulnerability against flood (Dawson et al., 2011; Meyer, Priest, & Kuhlicke, 2012). However, if endangered locations have already been developed, it is recommended that the administration should fund acquisition of land and structures at risk from willing sellers in the floodplain (Kundzewicz, 2002).

2.4.4 Risk spreading (e.g. insurance)

Risk spreading redistributes the cost of damage across the population and through time to reduce the potential loss from flooding. (Abbas, Amjath-Babu, Kächele, & Müller, 2015; Dawson et al., 2011). These mechanisms are needed in order to help flood victims recover after losses. Post-flood recovery is often less spectacular than actions during flood, as national leaders and the media who have left the natural catastrophe area become disinterested (Kundzewicz, 2002).

In this research, the drainage upgrade and WSUD would be used as candidate strategies while the land-use planning would be used as a spatial restriction in the model. Some non-structural options such as risk spreading would not be modelled as it has no direct relation to all goals (e.g. flooding) but could be considered as a compensation of certain goals (e.g. economic function).

2.5 Tools for Infrastructure Planning

A review on available infrastructure planning tools was carried out in this section to investigate the applicability and opportunities of existing method on long-term planning for multiple objectives with multiple strategies determined above.

The tools were classified into three categories, the synectic approaches, the statistic approaches and the exploring approaches, with the engagement of computation increase from none to highly. The development history of these tools and their gaps in application were summarized at the end of this section.

2.5.1 Synectic approaches

Perspective Method

'Perspectives method', derived from Cultural Theory (Thompson, Ellis, & Wildavsky, 1990) helps to classify, analyse and explore changing perspectives and according social response. A 'perspective' is a consistent description of the perceptual screen through which people interpret the world, and which guides them in acting. Some researchers also adopt it in water management as well as flood management, describing people's dynamic view on the value of water/impact of flood and how they should be managed (Haasnoot, Middelkoop, Offermans, Beek, & Deursen, 2012).

In application to water researches, three stereotypical perspectives are usually distinguished, focusing either on environment (Egalitarian), control (Hierarchist) or economy (Individualist).

To start with, both a world view (how people interpret the world) and a management style (how they act upon it) is comprised for each perspective and gathered in a table. By making different combinations of worldviews and management styles, a matrix of perspective-based scenarios can be developed, or existing scenarios can be interpreted and tested. A so-called perspective map can later be used to present trade-offs strategies considering two or more perspectives as well as how people's perspectives changes through time. Analysis on existing plans, policy papers, scenario studies and other documents as well as expert meetings, interviews and workshops are needed to work out these maps.

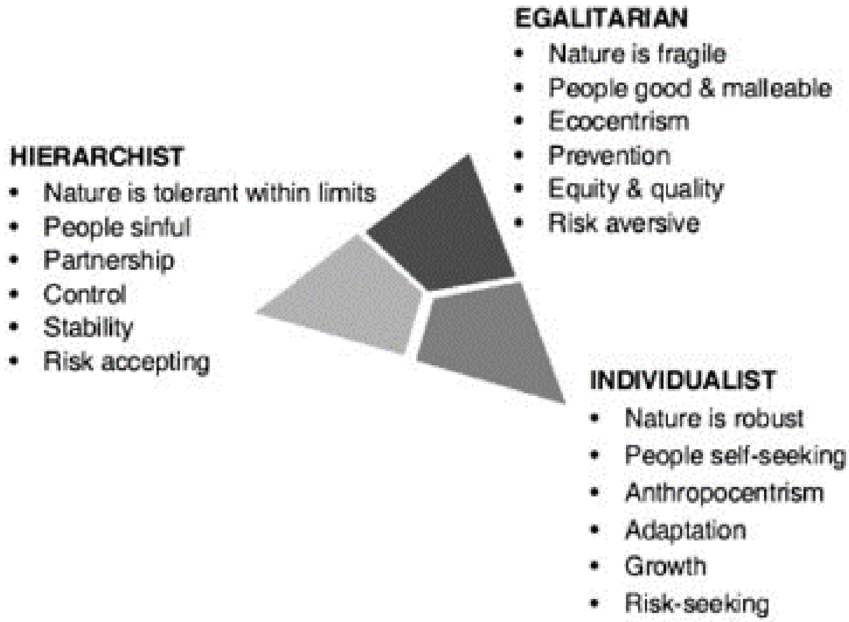

Figure 2.2 Perspective settings of the Perspective Method (Haasnoot et al., 2012)

(Middelkoop et al., 2004) structured climate, land use and socio-economic scenarios, as well as water management strategies with the Perspectives method in the Rhine and Meuse Rivers and generated a series of integrated scenarios. The water systems were evaluated and compared under different possible futures, considering the risk, cost and benefits of different strategies. Results demonstrate that, at the scale of the entire Rhine basin, the influence of climate change on extreme floods is much stronger than the influence of land use changes. Flood risk management in the lower river deltas should not fully rely on flood mitigation measures in the upstream basin. It also becomes clear that no flood risk management strategy is superior in all respects and in all circumstances. Under changing climate conditions, the present-day type of management in the lower river reaches runs the risk of becoming an expensive attempt to fully control flood risk problems, while trying to avoid real choices, without actually solving the problems in a long-term view.

Figure 2.3 Strategy analysis of the Perspective Method (Haasnoot et al., 2012)

(Offermans, Haasnoot, & Valkering, 2011) applied perspective method to analyse the response to future social and water events and the future social acceptance of different water management strategies. The result of perspective mapping was imported into an Integrated Assessment Meta Model (IAMM) to generate scenarios and integrated them with information of the water system into storylines. These storylines were evaluated for their social and physical robustness and their capacity to adapt to changing conditions. Results indicates that the scale of uncertainties are important for decisions on water management strategies and the performance for strategies for the nearby future is mainly determined by climate variability, while for the longer term (>50 years) climate change is important to take into account. A sustainable strategy could then be a strategy that is robust for climate variability (fluctuations within the climate) and social change in the near future, and flexible enough to adapt to climate change (fluctuations between different climates) and social change in the long term.

The Adaptive wheel

The Adaptive wheel was first designed in 2007 to assess in which way the institutions (formal governmental policies and informal social patterns of engagement) stimulate the capacity of society to adapt to climate change.

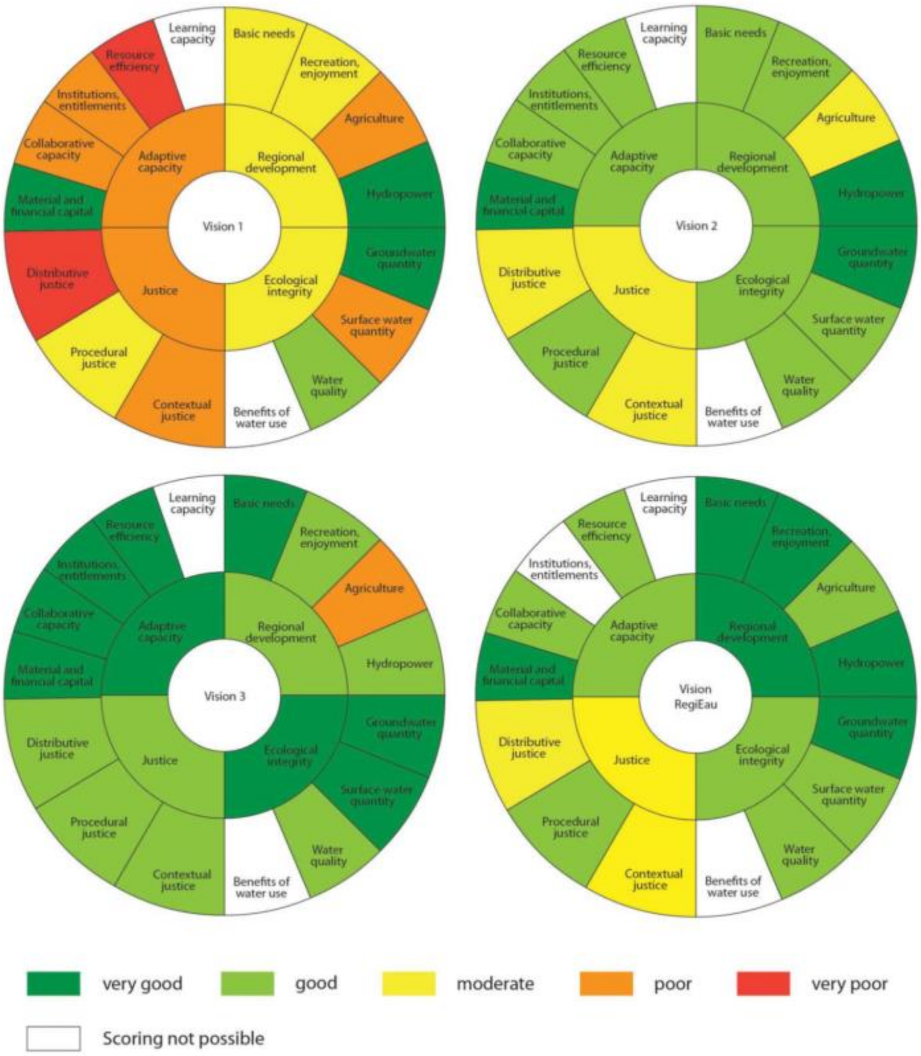

Figure 2.4 Different scenarios and analysis from The Adaptive wheel (Gupta et al., 2010)

The inner circle of the wheel shows the adaptive capacity as a whole, the middle circles shows the dimensions and the outer-circle shows the criteria. By applying colours to distinguish between high to low adaptive capacity, this wheel may be used to both assess and inform social actors about how their institutions influence different aspects of adaptive capacity and where there may be room for discussion and reform. These information will be collected into a story to communicate the strengths and weaknesses of a specific institution or institutional context in terms of adaptive capacity.

(Gupta et al., 2010) carried out a case study in which the Adaptive Capacity Wheel was used to assess the performance of institutions in the Dutch urbanized municipalities of Delft and Zaandam with respect to sharing responsibilities for rainfall and ground water management between residents and government actors. The wheel was formed with six dimensions: variety, learning capacity, room for autonomous change, leadership, availability of resources and fair governance as well as their 22 criteria. Data was collected through in-depth interviews with nineteen stakeholders involved in the municipalities' local water management. Result of such a wheel leads to a discussion on how institutions can enhance the adaptive capacity of society in a particular context. The colours in the wheel immediately identify areas in which the institutions do not encourage adaptive capacity, and the explanation of the researcher can help to better understand why institutions are not functioning well in those areas and what can be done to improve their impact on the adaptive capacity of society.

On the basis of Adaptive Wheel, (Schneider et al., 2014) present a conceptual and methodological approach for interdisciplinary sustainability assessments of water governance systems called the Sustainability Wheel. The approach combines transparent identification of sustainability principles, their regional contextualization through sub-principles (indicators), and the scoring of these indicators through deliberative dialogue within an interdisciplinary team of researchers, taking into account their various qualitative and quantitative research results. A case study was done on a complex water governance system in the Swiss Alps. Besides the current situation, four visions of different future develop strategies (growth, stabilization, moderate and RegiEau group) are also analysed and compared. The result indicates that the approach is advantageous for structuring complex and heterogeneous knowledge, gaining a holistic and comprehensive perspective on water sustainability, and communicating this perspective to stakeholders.

2.5.2 Statistic approaches

Assumption-Based Planning

Assumption-Based Planning (ABP), initially developed by RAND in the 1990s to solve a US Army strategic planning problem, has been used as a post-planning tool in many other projects that deals in a structured way with uncertainty in an existing plan.

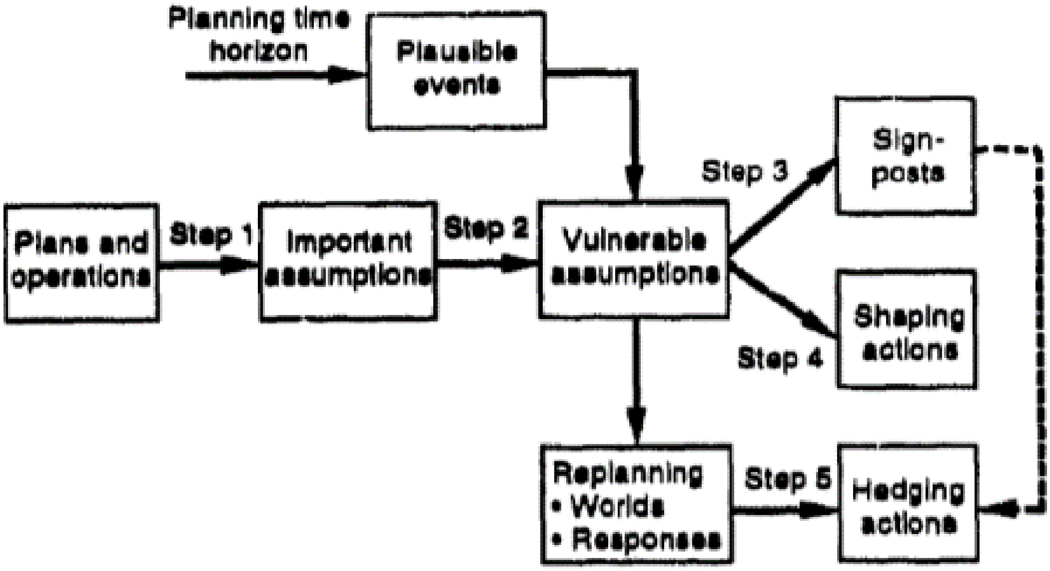

Figure 2.5 Workflow of the Assumption-Based Planning (Dewar, Builder, Hix, & Levin, 1993)

It follows a five-step procedure: 1) identify important assumptions; 2) identify assumption vulnerabilities; 3) define signposts; 4) define shaping actions and 5) define hedging actions. These steps do not necessarily depend on all the preceding steps as Figure 4.4 shows. Signposts are an indication that an assumption is becoming more vulnerable or is failing. Shaping actions are intended to exert what control the organization has over the vulnerability of those assumptions. Hedging actions are those actions that should be taken before the world of the violated assumption is projected to come about, to preserve organizational options or to prepare for that world(Dewar et al., 1993).

(Taneja, Walker, Ligteringen, Van Schuylenburg, & Van Der Plas, 2010) proposed a combination approach of ABP and Adaptive policymaking and applied it to a port expansion plan of Rotterdam in The Netherlands. ABP was used to examine the existing plan and identifying underlying assumptions as well as finding out the load-bearing and vulnerable assumptions. Adaptive

Policymaking was then used setting up actions against vulnerability and opportunity and contingency planning in case of failure. Result shows this manages to identify the uncertainties in an existing plan, and subsequently improves its robustness through taking actions either in the planning stage, or by preparing actions in advance that can be taken as knowledge is gained about the future world, thereby achieving successful outcomes across a variety of futures.

(Hermans, Naber, & Enserink, 2012) combined Dynamic Actor Network Analysis (DANA) with assumption-based planning to address dynamics related to long-term monitoring on water management. ABP is used to identify critical elements for monitoring as well as planning the monitoring process and setting signposts and triggers. One of the main conclusion about ABP is that there are certain difficulties in identifying useful indicators and expectations of their development over time. Thus, although the concepts of critical assumptions, signposts and triggers are useful and simple, their application in practice requires quite some effort.

Robust Decision Making

Robust Decision Making (RDM) was originally developed by (Robert J. Lempert, Groves, Popper, & Bankes, 2006). The approach aims to “design robust strategies from the information in computer-simulation models and to identify vulnerabilities, opportunities, and trade-offs among these strategies systematically”. It provides an iterative, analytic decision support methodology, often embedded in a process of participatory stakeholder engagement, intended to support decisions under conditions of “deep uncertainty”.

RDM also follows a five-step procedure:

1) Identify the initial candidate robust strategies, by either decision-makers’ preference or ranking by performance;

2) Identify vulnerabilities, by searching one or more clusters of future states where candidate strategies performs poorly;

3) Suggest hedges against vulnerabilities, by suggesting a relatively small set of alternative strategies that address the vulnerabilities of candidate ones;

4) Characterize deep uncertainties and trade-offs among strategies, the trade-off curve are presented for strategy choices in Step 3 and decision makers can use this information to choose a new candidate robust strategy and to characterize the deep uncertainties most important to their decision;

5) Consider Improved Hedging Options and Surprises, by repeating Step 1 to 4 with different candidate strategies.

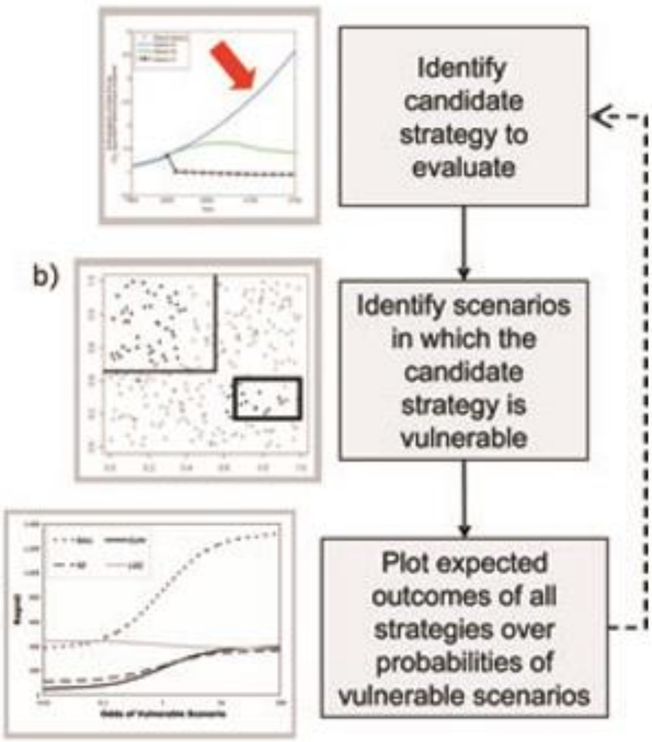

Figure 2.6 Workflow of the Robust Decision Making (Robert J. Lempert et al., 2006)

(Matrosov, Padula, & Harou, 2012) applies RDM to the UK's Thames water resource system with stochastic simulation and regret analysis to investigate the robustness of different supply and demand management scheme portfolios for the system. Future hydrological inflows, water demands and energy prices are considered explicitly for estimated future conditions. Study reveals some limitation of RDM such as possibility of missing better portfolios and time-consuming in computation, as well as benefits like evaluating the effect of multiple dimensions of uncertainty and explicitly simulating the nonlinear interactions between different supply and demand management schemes.

(Kim & Chung, 2014) developed an index-based robust decision making framework for watershed management dealing with water quantity and quality issues in a changing climate. Alternative development was generated and filtered taking consideration watershed component, residents' preferences on water management demands, and vulnerability of different management. These alternatives were then prioritized based on a minimax regret strategy for robust decision. The proposed procedure was applied to the Korean urban watershed, which has suffered from streamflow depletion and water quality deterioration. Result shows that the framework provides a useful watershed management tool for incorporating quantitative and qualitative information into the evaluation of various policies with regard to water resource planning and management.

(Casal-Campos, Fu, Butler, & Moore, 2015) developed a regret-based approach to robust decision making. Instead of using system performance as the indicator, the proposed approach evaluates strategies by assessing their relative performance loss (i.e., regret) across all impact categories and future scenarios. "Regret" of a decision (i.e., by selecting a specific drainage strategy) is defined as the missed opportunity to choose an alternative path of action which would have resulted more beneficial once the future is revealed. Thus, the basis of the method is to select the strategy that minimizes the opportunity loss or regret accrued from all the considered future states. With a case study on a range of watershed-scale "green" and "gray" drainage strategies under four socio-economic future scenarios, the concept proves to be useful in identifying performance trade-offs and recognizing states of the world most critical to decisions.

(Singh, Reed, & Keller, 2015) introduced a many-objective robust decision making (MORDM) framework that allows decision makers to pose multiple objectives, explore the trade-offs between potentially conflicting preferences of diverse decision makers, and to identify strategies that are robust to deep uncertainties. The framework employs multi-objective evolutionary search to identify trade-offs between strategies, re-evaluates their performance under deep uncertainty, and uses interactive visual analytics to support the selection of robust management strategies. MORDM was demonstrated on a stylized decision problem posed by the management of a lake in which surpassing a pollution threshold causes eutrophication. Results indicates the MORDM framework enables the discovery of strategies that balance multiple preferences and perform well under deep uncertainty. On the base of this framework, (Hadka, Herman, Reed, & Keller, 2015) introduces a new open source software to support this bottom-up environmental systems planning called OpenMORDM.

(Daron, 2014) investigated the challenges and opportunities in introducing robust decision making to the planning process in developing countries. A case study on plan to prevent railway infrastructure against sea level rise was carried out in South Africa with both traditional predict-then-act framing and RDM assess-risk-of-policy framing. Result shows that RDM can improve on predict-then-act approaches in helping to better identify those uncertainties which are important to a specific decision, removing unnecessary analysis of irrelevant variables. Adopting the RDM approach should also reduce the risk of implementing decision strategies that are prone to projection errors. Nevertheless, the complex realities of decision making processes, the need to combine quantitative data with qualitative understanding and competing environmental, socio-economic and political factors all pose significant obstacles to the full adaptation of RDM in developing countries like South Africa.

Info-gap

Info-gap, first developed by (Ben-Haim, 2006), begins by constructing a representation of the severe uncertainty, which it then uses to estimate the consequences of alternative strategies provided exogenously to the analysis. The approach informs decision-makers by providing them trade-off curves that compare these strategies according to two criteria it calls “robustness” and “opportuneness.”

(McCarthy & Lindenmayer, 2007) used info-gap decision theory to explore the relative economic benefits of revegetating the catchment with exotic plantations or native vegetation under the uncertain impact of water yield and the risk of wildfire. Coping these non-probabilistic sources of uncertainty with info-gap, results show the horizon of uncertainty in info-gap methods is unbounded while it is bounded to specific limits in, for example, min-max approaches and interval analysis. Info-gap methods consider trade-offs between the performance parameters and robustness to uncertainty instead of between different performance parameters.

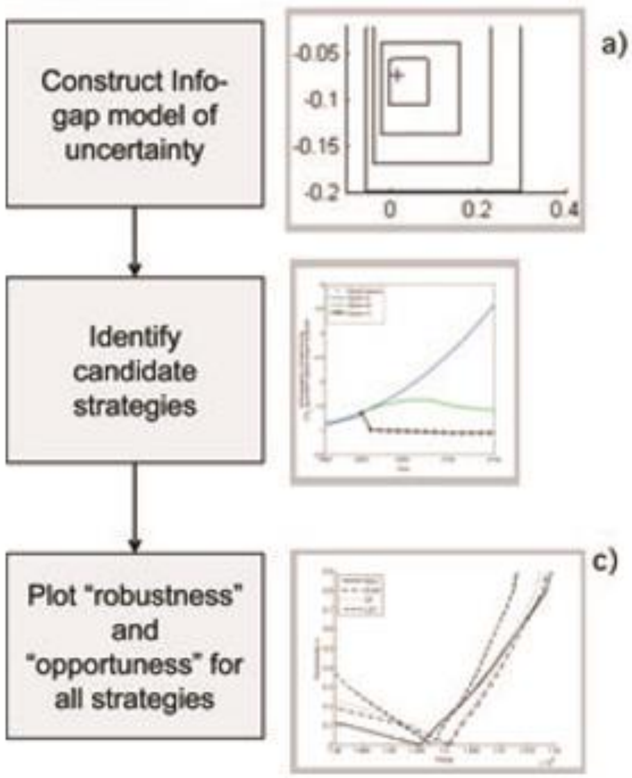

Figure 2.7 Workflow of the Info-gap (Ben-Haim, 2006)

(Chisholm & Wintle, 2012) applied info-gap theory to an ecosystem services trade-off case study in South Africa. Two alternative land uses strategies are tested, native vegetation conservation and exotic timber plantation, to maximize ecosystem service investment returns. The uncertain variables are the carbon price and the water price. Results indicates the outcome of info-gap analyses can be sensitive to the choice of uncertainty model. With a ‘‘no-information’’ uncertainty model that assumes equal relative uncertainty across both variables, info-gap theory identifies a minimally acceptable reward threshold above which conservation is preferred. However, with an uncertainty model that allows the carbon price to be substantially more uncertain than the water price, conservation of native vegetation becomes an economically more robust investment option than establishing alien pine plantations.

(Hall et al., 2012) used both Info-gap and RDM to evaluate alternative paths for climate-altering greenhouse gas emissions given the potential for nonlinear threshold responses in the climate system and a variety of other key parameters. The study finds that the two approaches reach similar but not identical policy recommendations. Info-gap explicitly considers both the potential gains if conditions turn out better than expected alongside losses if they turn out worse, which RDM does not. However, RDM can identify cases representing each situation and enable decision makers to trade one against the other. In addition to that, info-gap does not have any rules for balancing between robustness and most opportuneness, it asks decision makers to set minimum and aspirational performance levels and to favour the strategies that meet these levels. On the contrary, RDM considers imprecise probabilities and suggests probability thresholds ascribed to a scenario that might cause a decision maker to choose an alternative strategy.

(Matrosov, Woods, & Harou, 2013) apply both Info-gap and RDM to a water resource system planning problem: London's water supply system expansion in the Thames basin. The methods help identify which out of 20 proposed water supply infrastructure portfolios is the most robust given severely uncertain future hydrological inflows, water demands and energy prices. Multiple criteria of system performance are considered: service reliability, storage susceptibility, capital and operating cost, energy use and environmental flows. Initially the two decision frameworks lead to different recommendations. Result suggested the two methods are complementary and can be beneficially used together to better understand results.

(Korteling, Dessai, & Kapelan, 2012) utilises an integrated method based on Information-Gap decision theory and Multi-Criteria Decision Analysis to quantitatively assess the robustness of various water supply side and water demand side management options over a broad range of plausible futures. Findings show that beyond the uncertainty range explored with the headroom method, a preference reversal can occur, i.e. some management options that underperform at lower uncertainties, outperform at higher levels of uncertainty.

2.5.3 Exploring approaches

Adaptation Tipping Points

(Kwadijk et al., 2010) introduced the concept of 'adaptation tipping points', which is reached when the magnitude of change is such that the current management strategy can no longer meet its objectives. It involves the five steps below(B. Gersonius et al., 2012).

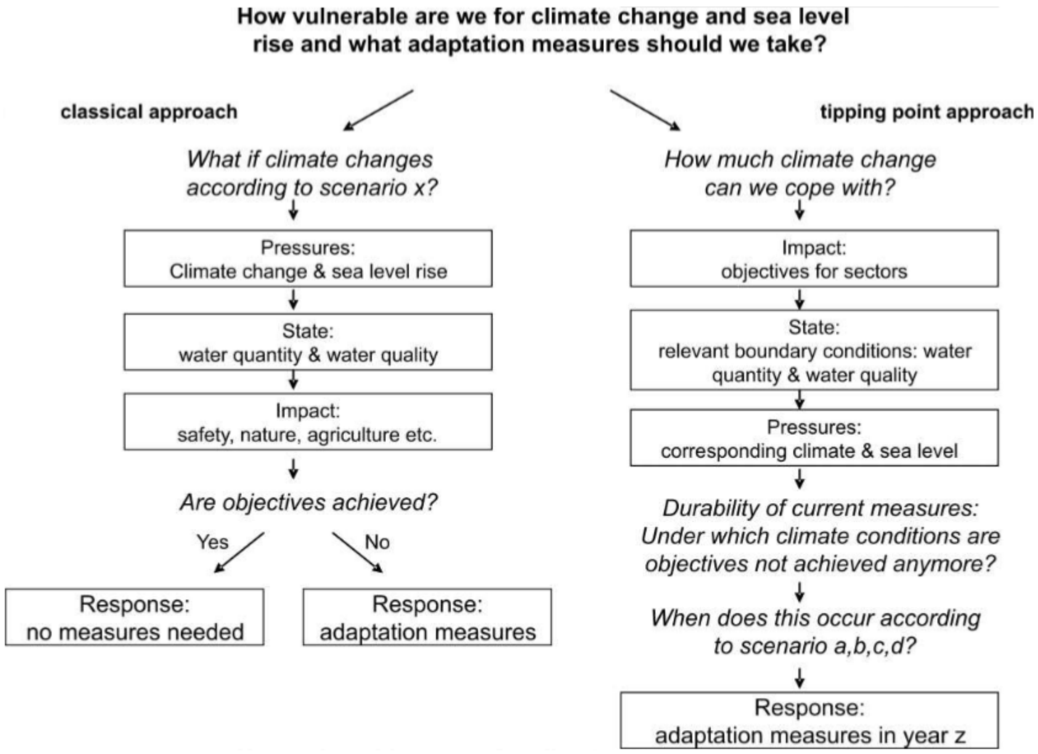

Figure 2.8 Comparison of classical decision making and Adaptive tipping point decision making (Kwadijk et al., 2010)

1. Specify the functions and uncertain parameters of interest. The objectives for these functions (acceptable standards) as well as candidate strategy are also defined.

2. Quantify the particular threshold values for the acceptable standards. These threshold values can be defined either according to regulations (e.g., by national law) or decided by the stakeholders involved and can change over time.

3. Identify the ATPs by assessing the specific boundary conditions (i.e., the system state) under which acceptable standards may be compromised.

4. Use climate change scenarios to transform the specific boundary conditions under which an ATP will occur into an estimate of when it is likely to occur (an estimate of the earliest and latest times that the performance of a strategy is no longer acceptable).

5. If it is desired that an ATP should not be reached, alternative and adaptive strategies will be needed to enhance climate change resilience.

(Kwadijk et al., 2010) used ATPs method as a bottom-up approach to assess capacity and vulnerability of the current water management system to climate change and sea level rise before failure, the two questions “what are the first issues that planner will face as a result of climate change” and “when can they expect that” are answered. A case study for long-term water management planning, which mainly focus on flood defence, drinking water supply and protection of the Rotterdam Harbour in the Netherlands is carried out. Results indicates less dependency on climate projections in ATPs than a traditional top-down approach starting from climate scenarios. In addition, ATPs analysis provides a lot of information about the system and its weaknesses.

(B. Gersonius et al., 2012) introduced a hybrid method called “Mainstreaming method”, to facilitate mainstreaming adaptation of stormwater systems to climate change. The approach starts with an analysis of adaptation tipping points (ATPs). The extension concerns the analysis of adaptation opportunities besides climate change in the stormwater system such as the ‘normal’ maintenance, modification or renewal of infrastructure, buildings and public spaces. The results from both analyses are then used in combination to identify and exploit Adaptation Mainstreaming Moments (AMMs). A case study in Netherlands was carried out with the proposed hybrid method to the management of flood risk for an urban stormwater system. Results shows this method will enhance the understanding of the adaptive potential of stormwater systems and helps to increase the no-/low-regret character of adaptation.

Adaptive Policy Making

(Walker, Rahman, & Cave, 2001) first proposed this approach to cope with the uncertainties that confront them by creating policies that respond to changes over time and that make explicit provision for learning. The approach makes adaptation explicit at the outset of policy formulation. Thus, the inevitable policy changes become part of a larger, recognized process and are not forced to be made repeatedly on an ad hoc basis. The approach involves the following three steps:

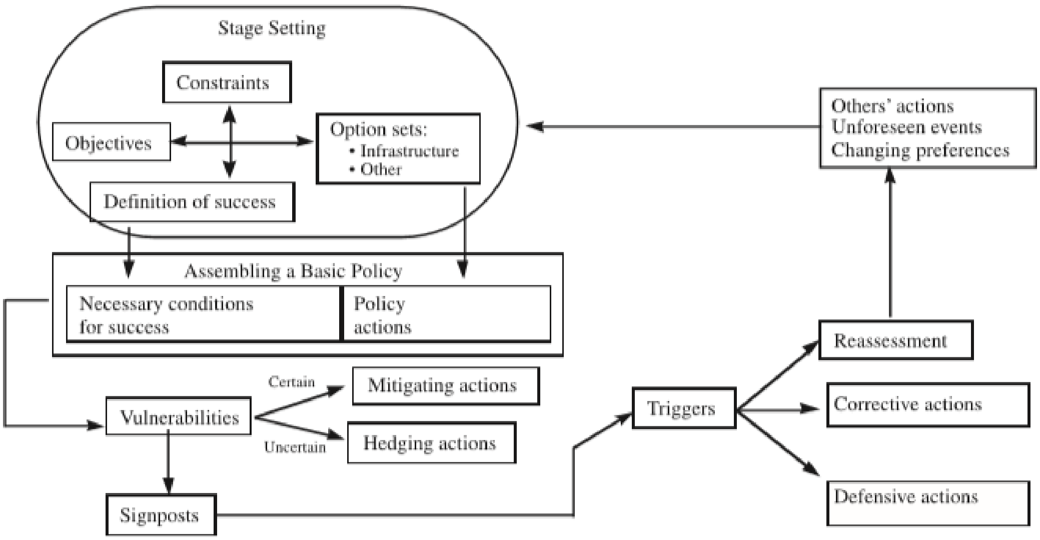

Figure 2.9 Workflow of the Adaptive policy making (Walker et al., 2001)

Set the stage. Objectives, constraints, and available policy options are specified or discussed in this step and come out with a definition of acceptable success.

Assemble the basic policy. Promising strategies are specified at this step, as well as identification of the necessary conditions for success.

Identify the vulnerabilities and design actions. Vulnerabilities can reduce acceptance of the policy to the point where its success is jeopardized. To address that, mitigating actions are designed for certain vulnerabilities and can be put in place immediately. Various hedging actions are developed, in anticipation of uncertain vulnerabilities, to diversify or reduce exposure or cushion the consequences.

Translate signposts and set up triggers. Signposts should be monitored in order to be certain that the underlying analysis remains valid and additional actions are taken in a timely and effective manner. The critical levels and appropriate contingency plans that make up the triggers should also be specified in this step.

To design well-functioned adaptive strategies, (Swanson et al., 2010) suggested the following seven methods:

1) using integrated and forward-looking analysis;

2) monitoring key performance indicators to trigger built-in policy adjustments;

3) undertaking formal policy review and continuous learning;

4) using multi-stakeholder deliberation;

5) enabling self-organization and social networking;

6) decentralizing decision making to the lowest and most effective jurisdictional level;

and 7) promoting variation in policy responses.

(Kwakkel, Walker, & Marchau, 2012) assessed the efficacy of Adaptive Policy Making for guiding the long-term development of infrastructure. The performance of a dynamic adaptive plan is compared with the performance of a static, rigid implementation plan across a wide spectrum of conceivable futures. Results reveal that the static rigid plan outperforms the dynamic adaptive plan in only a small part of the spectrum. Moreover, given the wide array of possible futures, the dynamic adaptive plan has a narrower spread of outcomes than the static rigid plan, implying that the dynamic adaptive plan exposes planners to less uncertainty about its future performance despite the wide variety of uncertainties that are present.

(Hamarat, Kwakkel, Pruyt, & Loonen, 2014) used multi-objective robust simulation optimization to specify appropriate conditions for adapting a policy, by identifying conditions that produce satisfactory results across a large ensemble of scenarios. A case study on EU energy case is demonstrated using a multi-objective evolutionary optimization technique, the Non-dominated Sorting Genetic Algorithm-II (NSGA-II), with adaptive policy making. Results shows the optimization helps in identification of appropriate triggers for actions through computational methods instead of best guesses or historic data.

Adaptation Pathways

(Haasnoot et al., 2012) developed the Adaptation Pathways method on the basis of adaption tipping points (Kwadijk et al., 2010). Pathway emerges when reaching a tipping point, and additional actions are needed. This approach presents a sequence of possible actions after a tipping point in the form of trees. It uses computational scenario approaches to assess the distribution of the sell-by date of several strategies across a large ensemble of transient scenarios. Rather than taking a one-off decision now about a 'best' option, the approach encourages the decision maker to postulate ''what if'' scenarios and to take a more flexible approach.(Ranger, Reeder, & Lowe, 2013)

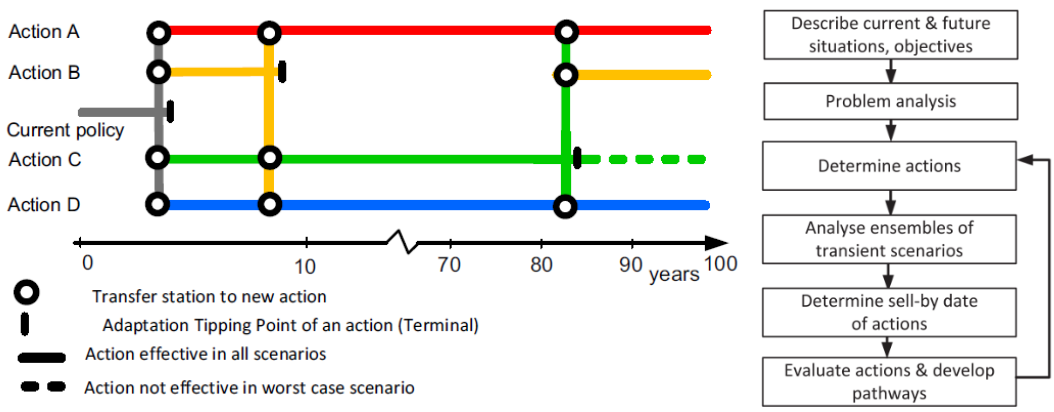

Figure 2.10 Workflow of the Adaptation Pathways (Ranger et al., 2013)

(Haasnoot et al., 2012; Haasnoot, Middelkoop, van Beek, & van Deursen, 2011) first developed this method using multiple realisations of transient scenarios with an Integrated Assessment Meta Model (IAMM). A hypothetical case study was carried out to illustrate the application. Simulated with three climate scenarios and thirteen policy options, the robustness of policies are then analysed by comparing its performance with the ranges for the indicators of certain perspective. Pathways were generated by using the sell-by date of each option and their perspective-based targets on the basis of the assumption that, if a policy option no longer meets the targets, it is necessary to add, or to shift to another policy option.

(Ranger et al., 2013) apply the adaptation pathway in a performance-based way instead of timely way in the case of Thames Estuary 2100 Project. Each of the strategies is evaluated by the maximum sea level before it fails and the shift among strategies depends on the actually sea level where the uncertainty lies.

(Haasnoot et al., 2014) evaluates its IAMM model with approach of closed questions. The results show that the existing model fits the purpose of screening and ranking of policy options and pathways to support the strategic decision making. A complex model can subsequently be used to obtain more detailed information.

(Maru, Stafford Smith, Sparrow, Pinho, & Dube, 2014) found short-term responses to vulnerability can risk locking in a pathway that increases specific resilience but creates greater vulnerability in the long-term. Equally, longer-term actions towards increasing desirable forms of resilience need to take account of short-term realities to respond to acute and multiple needs of marginalized remote communities.

Dynamic Adaptive Policy Pathways

A new paradigm has been conceived that infrastructures should be planned with a strategic vision of the future, committing to short-term actions, under a framework to guide future actions so as to dynamically adapt over time to meet changing (unforeseen) circumstances (Haasnoot et al., 2013). To realize this, "Dynamic Adaptive Policy Pathways" was proposed base on the strong feature of "Adaptive Policy Making" and "Adaptation Pathways": Think beforehand the actions and signposts of possible failure of a plan while monitor over time to trigger the actions. Visualizes sequences of possible actions through time, and includes uncertainties concerning societal values through perspectives. This approach involves nine steps:

1) Describe the study area, including the system's characteristics, the objectives, the constraints in the current situation, and potential constraints in future situations. Like in APM, the result will be a definition of success.

2) Analyse the problem. The current situation and possible future situations, which are 'business as usual cases', are compared to the specified objectives to identify whether there are any gaps. Both opportunities and vulnerabilities are considered.

3) Identifies sufficient possible strategies, which can help meeting the definition for success. These actions can be specified in light of the opportunities and vulnerabilities, categorized according to the types of actions (i.e. shaping, mitigating, hedging actions).

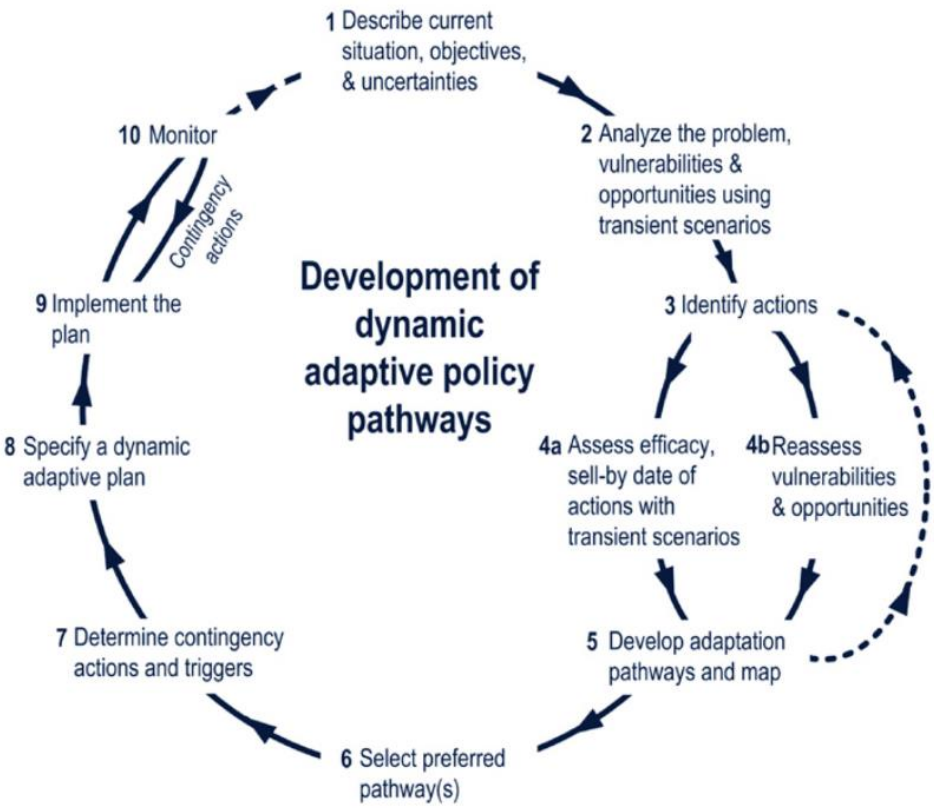

Figure 2.11 Workflow of the Dynamic Adaptive Policy Pathways (Haasnoot et al., 2013)

4) Evaluate the strategies. Sell-by date for each strategy is identified by assessing them individually on the outcome indicators for each scenario. The vulnerabilities and opportunities will be reassessed and repeat step 3 if needed.

5) Assemble of pathways. A pathway consists of a concatenation of strategies, where a new strategy is activated once its predecessor is no longer able to meet the definition of success.

6) Develop preferred pathways. Identify pathways that fit well within one or more specified perspective. Form the basic structure of a dynamic adaptive plan with these pathways.

7) Improve the robustness of the preferred pathways. Define actions to get and keep each of the pathways on track for success. Set up the monitoring system specifies what to monitor, and the triggers specify when a contingency action should be activated.

8) Translate the results into a dynamic adaptive plan, which specifies actions to be taken immediately, actions to be taken now to keep open future adaptations, and the monitoring system.

9) Implement the plan and establish the monitoring system. Signpost information related to the triggers is collected, and actions are activated, altered, stopped, or expanded in response to this information.

(Haasnoot et al., 2013) applied this approach on a long-term water management plan of the Rhine Delta in the Netherlands about the future arising from social, political, technological, economic, and climate changes. With the result of an adaptation pathways map with policy advisors and policymakers have shown an interest in the method as they suggest that the approach is comprehensive and more complex than a traditional scenario-strategy impact analysis for one or two points in the future and planners have experienced that plans change over time, and an adaptive strategy is an attractive idea for planners facing deep uncertainty.

(Kwakkel, Haasnoot, & Walker, 2015) developed a model-driven approach supporting the development of promising adaptation pathways. Possible futures over uncertainties related to climate change, land use, cause-effect relations, and policy efficacy are generate and candidate pathways are evaluated over this ensemble using an Integrated Assessment Meta Model.

Attention are focus on the robustness of the performance of the candidate pathways on multiple objectives, and a multi-objective evolutionary algorithm are used to find these promising pathways. Result supports that this approach is useful for supporting the development of dynamic adaptive plans. Through this method, a subset of most promising pathways are successfully identified. Moreover, some of these pathways contain solutions that had been discarded in earlier research.

2.6 Conclusions of literature review and key knowledge gaps

The history and development of the current planning tools is summarised in Figure 2.12. A comparison of this tools is presented in Table 1, and then discussed in the subsequent sub-sections.

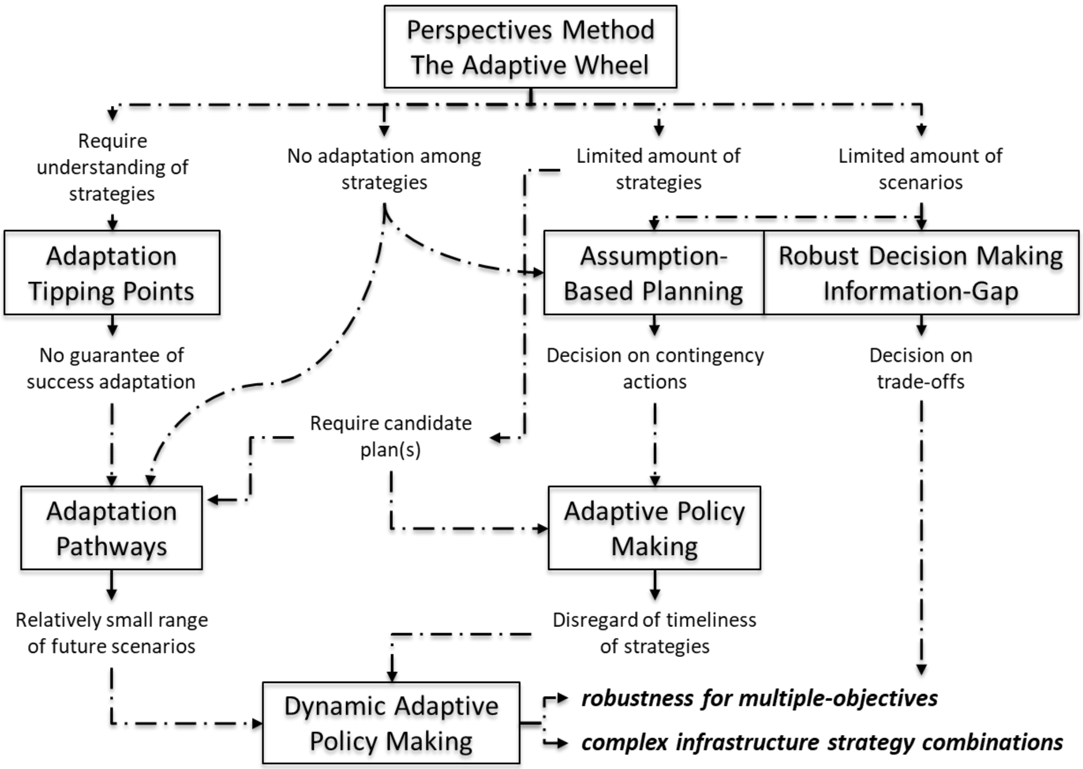

Figure 2.12 Development of existing long-term planning tools

Perspective method and Adaptive wheel both offer pre-assessed strategy options and helps the decision makers to find the better balanced one(s) when the future turns out to be at some place they assumed. Perspective method regards views from different groups of people while adaptive wheel is concerned on how different drivers influence strategies and their functions under plausible futures. These methods help to understand infrastructure planning through feedbacks, from social and technical systems, but have certain limitation on application as the analysis of either people's perspective or drivers of strategies mostly rely on the cognition of the researcher. Additionally, they offer mostly independent strategies which may be difficult to switchover in practice.

Table 1. Comparison of current planning tools

Planning Approach		Plans	Scenarios	Key advantages	Key gaps
Synectic Approach	Perspectives Method	Independent Strategies	Guessed Future	• Describe people's dynamic view over strategies and service they provide	• Can't guarantee feasible shift among strategies • Require understanding of strategies and perspectives
	The Adaptive wheel	-	Guessed Future	• Evaluate the key objectives and the weakness of the water system	• Need to design strategies • Subjective identification of objectives and indicators
Static Approach	Assumption-Based Planning	Candidate Plans	Guessed Future	• Identify the uncertainties in an existing plan • Improve the robustness of plans through contingency actions	• Difficult in identifying indicators and their expectations over time • Original plan and contingency actions are subjective
	Robust Decision Making	Candidate Plans	Interested Future space	• Evaluating the effect of multiple uncertainty • Simulating the nonlinear interactions between parameters • Enables decision makers to trade one plan against the other	• Possibility of missing better portfolios • Time-consuming in computation • Require quantitative data and qualitative understanding
	Info-gap	Candidate Plans	Interested Future space	• Consider trade-offs between the performance parameters and robustness to uncertainty	• Possibility of missing better portfolios • Time-consuming • Result is sensitive to the uncertainty model • Depends on decision makers to balance between robustness and opportuneness
Dynamic Approach	Adaptation Tipping Points	Candidate Plans	Future space	• Assess capacity and vulnerability of existing plans before failure • Provides information about the system and its weaknesses.	• No guarantee of successful adaptation • Require comprehensive understanding of strategies and adaptation plans
	Adaptive Policy Making	Independent Strategies	Future space	• Expose planners to less uncertainty about its future performance despite the wide variety of uncertainties that are present	• Difficulties in identification of appropriate triggers for actions • Possibility of missing better contingency actions • Regardless the timeliness of strategies.
	Adaptation Pathways	Independent Strategies	Future space	• Present possible actions after a tipping point in the form of trees • Encourage to take a more flexible approach	• Unable to evaluate with large range of future; • Short-term responses to vulnerability may lock in a pathway that increases specific

					resilience but creates greater vulnerability in the long-term.
	Dynamic Adaptive Policy Pathways	Independent Strategies	Future space	• Think beforehand the actions and signposts of possible failure • Monitor over time to trigger the actions • Visualize possible actions through time • Include uncertainty concerning societal values	• Unable to deal with complex infrastructure strategy combinations

Assumption-based planning tries to identify the vulnerability of plans under different situations and design contingency actions to overcome these weakness in case it happens. It offers better flexibility as well as resistance to uncertainties in long-term planning. Nevertheless, it still has the limitation of cognition on both scenarios and strategies as researchers might underestimate or unforeseen the vulnerability of plans as well as plausible events that may happen.

Robust Decision Making and Info-gap make an effort to overcome these kinds of cognitional issue by sampling scenarios within possible range of futures and assessing the performance of plans under all these conditions. The former method put more emphasis on where the strategies might fail and how to modify them to be more robust. The later one offers a trade-off between "robustness" and "opportuneness". Similar to assumption-based planning, these methods require a set of long-term plans that have been priori-designed and offers the optimizations on the basis of them. Although both of them tries to reduce the uncertainties in future scenarios, limitation still lies in the formulation of the initial plans as researchers usually design based on their understanding and estimation of strategies. There is a chance that we miss good plans from the beginning.

Adaptive tipping points works similar to robust decision making, it focuses on defining if and when the system will fail and adaptation strategies are needed, thus enabling policy makers to plan the adaptation. The difference is that the identification of ATPs by no means guarantees successful adaptation. It also share the limitation of possible lack of understanding or strategies.

With the help of more powerful computational resources and efficient algorithms, approaches like adaptive policy making and adaptation pathways start to explore both in uncertain scenario space and plausible strategy space. Adaptive policy making inherits the idea of assumption-based planning, using a user-defined standard of success instead of a manually analysis vulnerability, to assess all possible strategies under different scenarios, design contingency actions and reassess the whole plan to get a more robust solution. Adaptation pathways deals with the problem by evaluating the sell-by date of all possible actions from now on and formulate possible implementation pathways that leads to a successful ending. As these two method are complementary in a way that the former one (Adaptive policy making) didn’t consider the timeliness of strategies and the later one (Adaptation pathways) has low tolerance on unforeseen failure of strategies, a combination of both, Dynamic Adaptive Policy Pathways is also carried out that evolves both sell-by date of strategies and contingency options, to further reduce the uncertainty of future and design a more robust plan for decision makers. These approaches are breakthroughs in the field of long-term infrastructure planning as they take account of uncertainties both in strategies and future, but improvements can still be made as the strategies used in these methods are still independent and the planning itself usually concentrates on a single goal. Further researches to identify the cooperation effect of multiple-strategies as well as multiple-objectives are still needed to put these long-term planning approaches into more efficient practice.

The review of different bodies of literature deemed relevant for the research area of infrastructure planning, has allowed for a number of conclusions to be drawn out as well as insights into possible improvements of current planning-supporting method. Overall, the key findings of the literature review are summarised as follows:

An increasingly comprehensive infrastructure system is desired to provide multiple functions that meets the need of the society in consideration of not only the technical performance but also the economic and social benefits.

Besides the changing requirement of urban water infrastructures, with more unpredicted events happen, the challenge of uncertainties in future and strategies themselves has attracted more and more concerns. There is a need to support decision making in planning process to meet these needs.

Current planning support tools have gone through a process of continuous improvement, to overcome the limitation of cognition of researchers and workout a more robust plan for future. Yet there still need efforts to improve current approaches for more feasible and flexible plans.

2.7 Research questions

This research aims to develop methods for identifying robust water infrastructure implementation pathways to increase the resilience to the changing demand of water service, across the exploratory space for futures under deep uncertainty. Although the aim is to develop a general method that can be applied to all urban water streams (supply, sewage and drainage), the work will in the first instance focus on the adaptation of urban drainage system to assure a city’s flood resilience. The research will answer these questions:

1. In the planning of green infrastructures, how to improve the decision reliability under limited data availability and reduce the uncertainty of planners' subjective perceptions?

2. In the planning of grey infrastructures, how to comprehensively consider the influence of green infrastructure planning in different construction stages and to improve the robustness of grey-green systems?

3. How to deduce the urban development and the construction of complex drainage system, while identifying the problems in the long-term construction and operation process to generate a robust urban water implementation pathway?

4. How to improve the identification speed of urban water implementation pathway and improve the practicability of this method?

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Chapter 3.

Hierarchical fuzzy evaluation of spatial vulnerability and WSUD suitability in urban areas

3.1 Introduction

With the tremendous development in China over the past few decades, various problems resulting from rapid urbanization, population growth, and climate change have emerged. The failure of water drainage systems is one of the most common. Due to a low design capacity, a lack of maintenance, and a reduction in natural buffering areas, flooding and waterlogging caused by this failure are in turn causing huge losses in terms of both property and human lives.

The Sponge City concept was proposed in 2012 in China during the Low-Carbon Urban Development and Technology Forum to address the conflict between development and resilience cities face (Xia et al., 2017). Similar concepts in urban planning, such as Best Management Practices (Urbonas & Stahre, 1993), Low Impact Development (Fairlie, 1996), and Water Sensitive Urban Design (Wong & Brown, 2009) have been successfully practiced, but there is still a long way to go to adapt, improve, and develop proper techniques, strategies, and planning methods to meet local conditions and needs in China.

Followed by a barrage of government-issued policies, several cities in China with different population densities, spatial scales, and climate conditions are currently sponsored to explore the applicative national strategy and practice of Sponge City by the 2020s. Meanwhile, current Sponge City designs and construction plans do not satisfy our expectations (Xia et al., 2017). To achieve better performance and more cost-efficiency, it is urged that a proper decision-making method be employed in the planning process. Although many novel, powerful, and accurate models and tools to support decision making have emerged in recent years (Albano, Mancusi, & Abbate, 2017; Ferguson, Brown, Frantzeskaki, de Haan, & Deletic, 2013; Hall et al., 2012; Inam et al., 2017; Urich et al., 2012), most of them have been developed and used by experienced researchers or developers. It is almost impossible for lay designers and decision makers to correctly and easily apply those tools to their work.

Some widely used methods are usually simple and straightforward. One of the most commonly used decision support method is Multi-Criteria Decision Making (MCDM), which combines quantitative and qualitative criteria to form a single index of evaluation. Implemented in a Geographic Information System(GIS) environment, MCDM has been applied in various studies in spatial analysis or planning in areas such as resource management (Chang, Qi, & Yang, 2012), urban planning (Chen & Paydar, 2012; Jeong, García-Moruno, & Hernández-Blanco, 2013; R. Rahman & Saha, 2008; van Niekerk et al., 2016), and vulnerability assessment (Araya-Munoz, Metzger, Stuart, Wilson, & Carvajal, 2017; Pourghasemi, Moradi, Fatemi Aghda, Gokceoglu, & Pradhan, 2013; Radmehr & Araghinejad, 2015; M. R. Rahman, Shi, & Chongfa, 2014) over the last few decades. Such spatial-based MCDM involves a set of geographically defined basic units (e.g., polygons, or cells), and a set of evaluation criteria represented as map layers (Chen & Paydar, 2012). The criterion maps rank each unit with an overall score according to the attribute values and criteria weights using different analyzing approaches (e.g., Boolean overlay, weighted linear combination, and ordered weighted average) (R. Rahman & Saha, 2008). The Analytical Hierarchy Procedure (AHP) (Saaty, 1980) is a method widely used for ranking multi-criteria weights. It calculates the weighting factors using a pairwise comparison matrix where all relevant criteria are compared against each other with reproducible preference factors.

Another decision support method is Fuzzy Decision Making, which is a mathematical method for supporting decision making under uncertain situations with limited information (Zadeh, 1996). It consists in an inference structure that enables appropriate human reasoning capabilities. It has been widely applied in studies relating to vulnerability assessment (Araya-Munoz et al., 2017; G. Lee, Jun, & Chung, 2014; M.-J. Lee, Kang, & Kim, 2015; Radmehr & Araghinejad, 2015; Rezaei, Safavi, & Ahmadi, 2013; Şener & Şener, 2015; Singh & Nair, 2014) and urban planning (Gray et al., 2014; Navas, Telfer, & Ross, 2011; Talebian & Shafahi, 2015; Teh & Teh, 2011; Zhang, Wang, Chen, & Zhu, 2011). The approach sets up a fuzzy inference system (FIS), which consists in user-defined membership functions and decision rules (Zadeh, 1996). The value for each criterion is first divided into classes/words, and a membership function is used to identify the range of each class/word. Each class has overlay parts with adjacent classes to represent the fuzziness. The decision rules represent the ambiguous designing principle of the planner (e.g., if the imperviousness is low and the pollution productivity is high, then the vulnerability is high). The criterion maps rank each unit by allocating their input distribution in the membership function and finding out their output distribution according to the rule set and rule strength, which is called the Mamdani method (Sivanandam, Sumathi, & Deepa, 2007).

Realistically, the application of such methods requires a comprehensive understanding of the planning process as well as sufficient data. On one hand, the more data we have, the more comprehensive we can understand the situation and make more reliable decisions. On the other hand, the more data we are dealing with, the more subjective pairwise comparison matrixes (e.g., MCDM) or decision rules (e.g., FIS) we need to establish and therefore the more uncertain we are of the decisions. Nevertheless, the above method usually evaluates criteria units individually (especially polygons) and disregards the surrounding features.

In this study, we developed an easily applicable decision-making framework that applies a hierarchical FIS system (Şener & Şener, 2015) on a fuzzified GIS system, in order to offer better decision supports with fewer user-defined data. The hierarchical FIS system aims to reduce the subjective judgement from planners, minimizing uncertainty in the system. The fuzzified GIS system provides comprehensive information on the surrounding environment to support better decisions. The developed framework and the traditional MCDM method were applied on a planning program at Yangchen Lake Resort, Suzhou, Jiangsu, China. The results of both methods were compared so that the pros and cons for each approach could be analyzed.

3.2 Methods and Data Description

3.2.1 Site Description

The 61.7 km^2 Yangchen lake resort consists of two peninsulas, over which more than 100 inner rivers are spread (see Figure 3.1). About 3.5 km^2 of land area is used for various kinds of farming activities (rice, vegetable, fruit, and fishery) and 5 km^2 is used for public landscapes and parks. A new town is gradually developing at the upper end of the left peninsula.

Due to pollution from farming and a lack of maintenance, more than one-third of the inner rivers are blocked. The performance of the drainage system is poor in the town area as the town has been expanding for decades with the drainage system never upgraded/expanded.

The aim of the design is to offer decision support for Sponge City planning (where to introduce new techniques, cost-efficiency on adapting strategies, etc.), such that the retrofit impact in the area of the resort is minimized and the spatial planning of strategies is reasonable.

There are four candidate strategies: business as usual (BAU), rain tank or green roof (small scale system), rain garden or bioretention cell (large scale system), and re-planning.

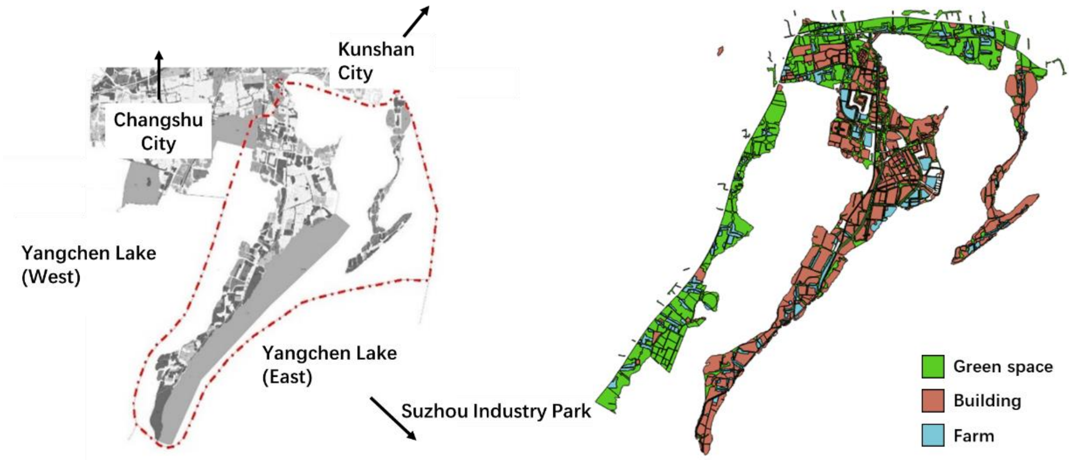

Figure 3.1 Case Study: Yangchen lake resort.

3.2.2 Data Collection and Criteria Selection

On the basis of a dwg map from the stakeholders, field investigations were carried out to gather information about land use, the source of pollution, and the environmental status on site. The dwg file was then transformed into a GIS map via ArcGIS, and these data were inputted into each polygon. Together with experienced designers, major criteria pertaining to permeability, pollution productivity, loss from flooding, and retrofit cost, were identified. Due to limitations in data accessibility, the four features are represented by 0, 1, and 2 (indicating low, medium, and high, for the degree of each criterion) for every polygon according to the designers' experience (see Table 3.1).

Table 3.1. Geographic Information System (GIS) features for the resort.

Land Use	Permeability	Pollutant Productivity	Loss from Flooding	Retrofit Cost
Farm	1	2	1	1
Building	0	1	2	2
Green space	2	0	0	0

(* 0: Low; 1: Medium; 2: High).

3.2.3 Methodology

We applied MCDM and HFIS in this case study according the following procedures (see Figure 3.2).

Multi-Criteria Decision Making with an Analytical Hierarchy Procedure

The MCDM process requires decision makers to rank the criteria based on pairwise comparisons. In this study, these comparisons were obtained from a survey of 25 experts that included members of the urban planning institute as well as academic experts specialized in urban planning. Each participant was asked to rank the criteria and class by referring to a numerical scale of 1–9, with a score of 1 representing indifference between the two criteria and 9 indicating a great amount of concern (R. Rahman & Saha, 2008).

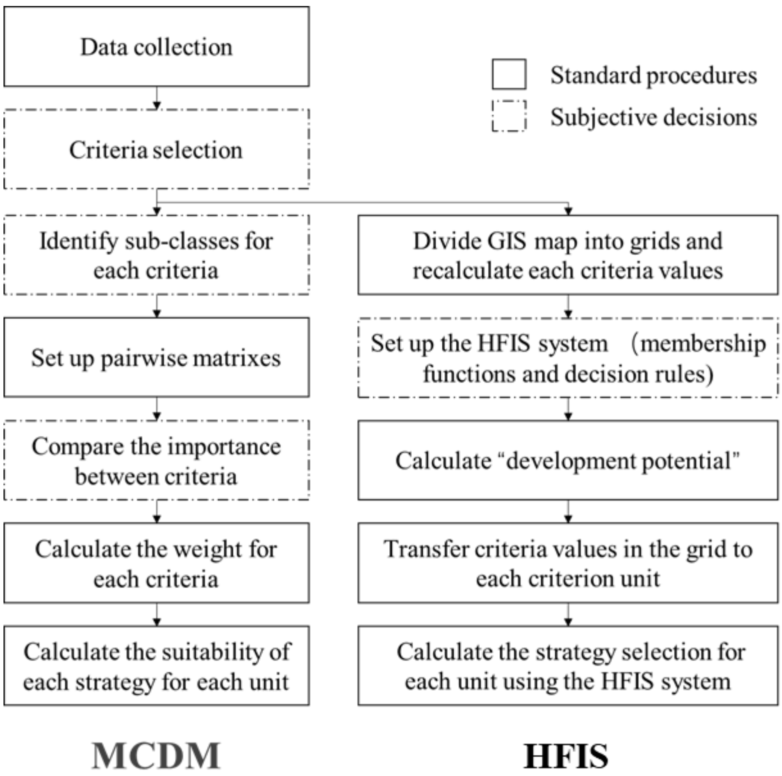

Figure 3.2 Multi-Criteria Decision Making (MCDM) and Hierarchical Fuzzy Inference System (HFIS) flow chart.

The final 25 pairwise comparisons matrixes were establish based on the mean value of all survey results. The weight for each criterion, class, and strategy were then calculated using the AHP method (see Figure 3.3). The consistency ratio (CR) was calculated to evaluate the consistency of pairwise comparisons. A standard CR threshold value of 0.10 was applied.

	Impervious ratio	Land Use	Area	Damage loss	Retrofit cost	Pollution
Impervious ratio		1	2	1/5	1/7	1/6
Land Use			2	1/4	1/5	1/4
Area				1/6	1/6	1/5
Damage loss					1	2
Retrofit cost						2
Pollution						

Figure 3.3 Pairwise comparisons matrixes of AHP method

After the factors, their weights, and all constraints in the decision tree were established for each strategy, the suitability of each strategy was calculated for each unit in the criterion map according to its criteria value (Suitability = Criteria Weight × Class Weight × Strategy Weight). The sponge urban planning map was generated by selecting the most suitable strategy for each unit.

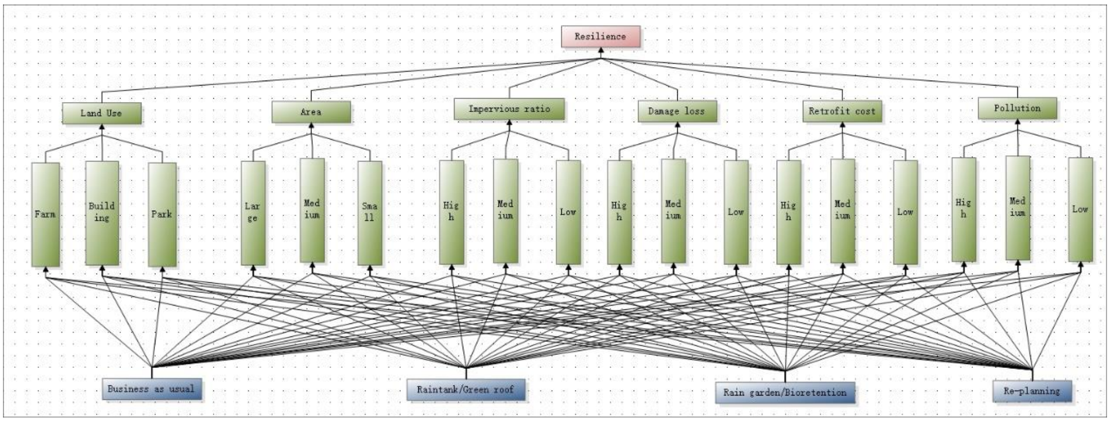

Figure 3.4 AHP structure

Hierarchical Fuzzy Inference System (HFIS) Decision Making

Step 1. "Fuzzification" of GIS Maps

As discussed before, a major goal of this framework is to provide comprehensive information from the surrounding environment for each criteria unit. Thus a "fuzzified GIS system" was designed to convert all polygon-based GIS layers and their criteria values into grid-based GIS layers. In this study, we first divided the resort into 100 m × 100 m (1 ha) grids. The size of the grids was determined considering the mid-value (0.55 ha) and distribution (<1 ha: 63%) of the polygon area in the GIS map. Such grids offered an adequate capacity of embracing characteristics of multiple polygons. Permeability, pollutant productivity, and loss from flooding was calculated for each grid according to the corresponding value in the polygon they intersected (Equation (1)).

$$I_{B,j} = \sum I_{A,j} \frac{a_i^{'}}{A_i^{'}} \frac{a_i^{'}}{1} \tag{1}$$

Where,

$I_{B,j}$ is the criteria value of grid j;

$I_{A,i}$ is the value of the corresponding criteria in polygon i;

a_i' is the intersect area of grid j and polygon i;

A_i' is the area of polygon i.

Step 2. Fuzzy Analysis

A Matlab (R2017a) toolbox, the Fuzzy Logic Designer, was used to set up the FIS based on the result from Step 1. The Gaussian Membership Functions are adopted for the following criteria to allow better deviation to these fuzzified values (see Figure 3.5). “Permeability” and “pollutant productivity” were first analyzed to evaluate the “vulnerability” of each grid. Together with the “loss from flooding,” the “vulnerability” went through the FIS again to calculate the “develop potential”. The calculation of the above functions are based on Mamdani method (Sivanandam, Sumathi, & Deepa, 2007). The advantage of using a two-layer fuzzy process instead of dealing with three parameters at a time (using permeability, pollutant productivity, and loss for flooding to directly analyze develop potential) is that the former requires fewer inputs. The two-layer fuzzy module requires two rule sets with 25 rules each (for two parameters with 5 value ranges, the minimum amount of rules will be 5 × 5), while the one-layer module would need a set of 125 rules. If fewer rules are designed, more uncertainty will be reduced from the cognitive limitation.

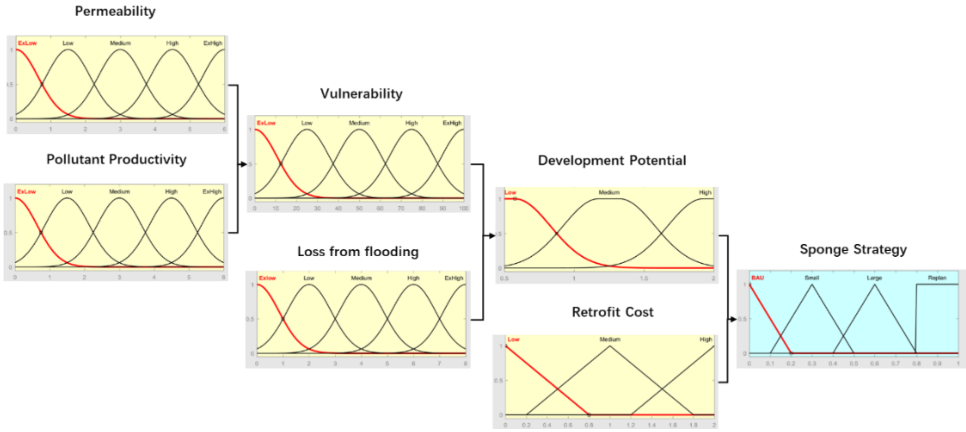

Figure 3.5 Designed membership functions of the hierarchical fuzzy inference system (FIS).

Step 3. “Defuzzification” of GIS Maps and Strategy Selection

In this stage, the grid map contains output on development potential of each grid, resulting from comprehensive consideration of spatial (Step 1) and cognitive (Step 2) factors. Such information is not helpful for planners as they are grid-based rather than polygon-based (each polygon is an individual unit that can be retrofitted, such as building, farmland, etc.). Thus, the grid map was translated to an original polygon-based GIS map through Equation (2) and Equation (3) so that the development potential for each polygon can be understood.

$$D_{A,i} = \sum D_{B,j} \frac{a_j'}{A_i} \tag{2}$$

$$A_i = \sum a_j' \tag{3}$$

Where,

$D_{A,i}$ is the development potential of polygon *i*;

$D_{B,i}$ is the development potential of grid *j*;

a_j' is the intersecting area of grid *j* and polygon *i*;

A_i is the area of polygon *i*.

A third fuzzy process was conducted with the development potential and retrofit cost, in the same way as Step 2, to determine the strategy to be chosen (business as usual, rainwater tank, rain garden, or re-planning). The Trapezoidal Membership Function are adopted in this step to allow crisper decision choices (see Figure 3). The strategy for each polygon was then calculated, assembled, and visualized as a sponge urban design map.

3.3 Results and Discussion

3.3.1 AHP Result

The result weight and consistency ratio is listed in Table 3.2 and 3.3 relatively.

The consistency ratio of all results are less than 0.1, indicating reliability of the result (R. Rahman & Saha, 2008). According to the analysis results, in the process of sponge city construction at the present stage, the main factors that planners consider are retrofit cost (0.3286), flood loss (0.2994) and potential pollution (0.2117) whose weight sum up to 0.8397, far higher than the other three factors.

The planners are tend to implement retrofit in areas with lower permeability, higher flood loss, lower retrofit cost, higher pollution potential, smaller area or which being used as farm land.

Table 3.2 Criteria tree and Analytical Hierarchy Procedure (AHP) results.

Goal	Weight	Criteria	Weight	Class	Weight	Strategy Weight: Business As Usual	Raintank Green Roof	Rain Garden Bioretention	Re-Planning
Development	1.0000	Permea-bility	0.0553	High	0.0754	0.6692	0.1155	0.1155	0.0998
				Medium	0.2290	0.2500	0.2500	0.2500	0.2500
				Low	0.6955	0.0871	0.3854	0.3854	0.1422
		Land use	0.0649	Farm	0.6955	0.0886	0.0952	0.5513	0.2649
				Building	0.2290	0.3812	0.4331	0.1030	0.0828
				Park	0.0754	0.6201	0.0708	0.2166	0.0925
		Area (ha)	0.0401	1.19–45	0.1140	0.3000	0.3000	0.3000	0.1000
				0.25–1.19	0.4054	0.2500	0.2500	0.2500	0.2500
				0–0.25	0.4806	0.2857	0.2857	0.2857	0.1429
		Flood loss	0.2994	High	0.7514	0.0445	0.1723	0.1958	0.5874
				Medium	0.1782	0.0813	0.3598	0.3598	0.1991
				Low	0.0704	0.3000	0.3000	0.3000	0.1000

		Retrofit cost	0.3286	High	0.0658	0.4167	0.0833	0.0833	0.4167
				Medium	0.2172	0.3000	0.3000	0.3000	0.1000
				Low	0.7171	0.3125	0.3125	0.3125	0.0625
		Pollution	0.2117	High	0.7429	0.0457	0.1451	0.3494	0.4598
				Medium	0.1939	0.0871	0.3854	0.3854	0.1422
				Low	0.0633	0.3313	0.2916	0.2916	0.0855

Table 3.3 Consistency ratio of the AHP analysis

Goal	CR	Criteria	CR	Class	CR	CR			
						Business As Usual	Raintank Green Roof	Rain Garden Bioretention	Re-Planning
Development	0.0226	Permea-bility	0.0735	High	0.0162	0.0028	0.0005	0.0005	0.0004
				Medium	0.0000	0.0032	0.0032	0.0032	0.0032
				Low	0.0077	0.0033	0.0148	0.0148	0.0055
		Land use	0.0735	Farm	0.0282	0.0040	0.0043	0.0249	0.0120
				Building	0.0520	0.0057	0.0064	0.0015	0.0012
				Park	0.0486	0.0030	0.0003	0.0011	0.0005
		Area (ha)	0.0279	1.19–45	0.0000	0.0014	0.0014	0.0014	0.0005
				0.25–1.19	0.0000	0.0041	0.0041	0.0041	0.0041
				0–0.25	0.0000	0.0055	0.0055	0.0055	0.0028
		Flood loss	0.0279	High	0.0370	0.0100	0.0388	0.0440	0.1321
				Medium	0.0077	0.0043	0.0192	0.0192	0.0106
				Low	0.0000	0.0063	0.0063	0.0063	0.0021
		Retrofit cost	0.0355	High	0.0000	0.0090	0.0018	0.0018	0.0090
				Medium	0.0000	0.0214	0.0214	0.0214	0.0071
				Low	0.0000	0.0736	0.0736	0.0736	0.0147
		Pollution	0.06850	High	0.0744	0.0072	0.0228	0.0550	0.0723
				Medium	0.0077	0.0036	0.0158	0.0158	0.0058
				Low	0.0123	0.0044	0.0039	0.0039	0.0011

3.3.2 Fuzzified GIS Map

Compared to the original GIS maps, the fuzzified maps present the same or less intensive criteria values in most areas (see Figure 3.4). This indicates that the fuzzification process under this gridding scale can maintain the dominant characteristics of the polygons while considering the surrounding environment and can make reasonable adjustments. Notably, the highlighted Areas A and B initially had the same attribute values but ended up with different fuzzified values. The reason for these differences results from the more intensive land use in Area A. Despite the same land use type, there were more scattered green spaces and inner rivers within Area B. The fuzzified GIS map proved to be efficient in revealing this non-significant information, which influences the final decision.

3.3.3 WSUD Plans

The result of the sponge urban planning map is presented in Figure 3.5. This map suggests that 55.6% (MDCM) or 49.7% (HFIS) of the resort can undertake the business as usual strategy. These areas include the majority of the west and north green spaces of the resort and the residential areas in the middle peninsula. These areas have relatively good permeability (by themselves or by adjacent to the lake), moderate pollutant productivity, or low loss from flood.

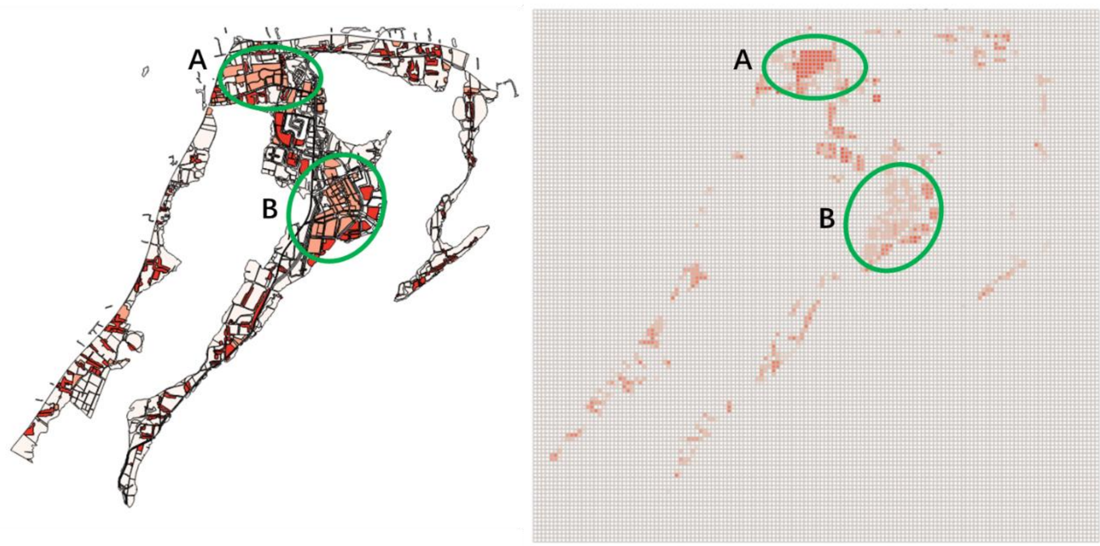

Figure 3.4 Example of a fuzzified GIS map (pollutant productivity).

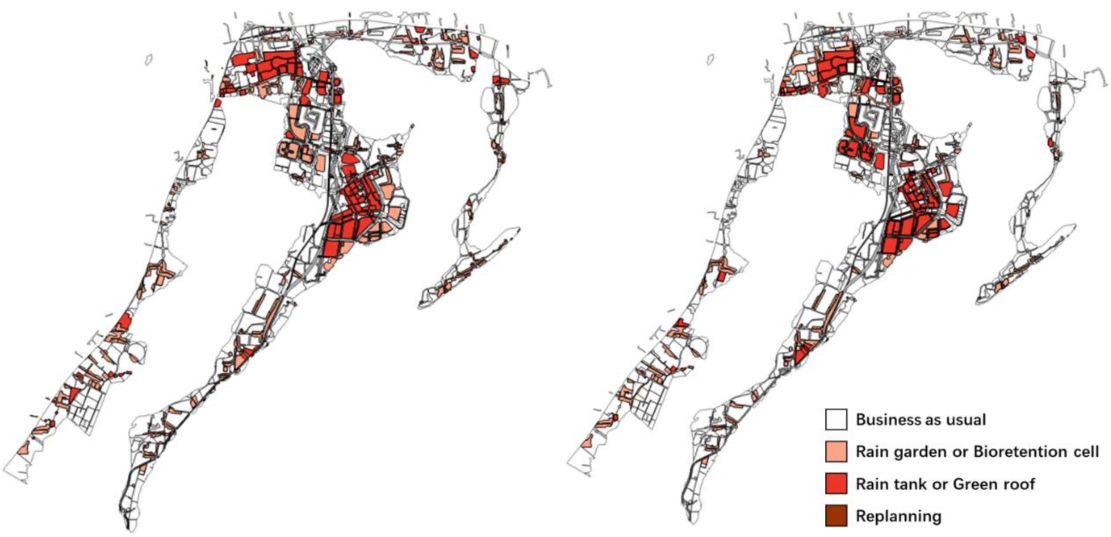

Figure 3.5 Sponge urban planning maps for MCDM (left) and hierarchical FIS (right).

It is also suggested that 22.7% (MDCM) or 28.7% (HFIS) of the resort apply rainwater tanks or green roofs. These areas consist of high-density buildings whose runoff contributes to the pollution in adjacent areas (such as farming).

The map further suggests that 21.7% (MDCM) or 21.6% (HFIS) of the resort have rain gardens or bioretention cells implemented. Most of these would be located in areas related to farming. The pollution from fish farming is extremely high, so it is advisable to take advantage of the reserved land and to construct a large-scale rain garden to hold and treat the runoff from the farming area.

3.3.4 Comparison of MCDM and HFIS

In this study, the two methods both require selection and identification of criteria and their classes' ranges. To generate a planning map, MCDM methods required the planners to fulfil 25 pairwise comparison matrixes, which consist of 141 manual evaluations for deciding the importance between two criteria to their upper level criteria. The three-level HFIS required to design 34 decision rules to determine which strategy was preferred under certain conditions.

Table 3.4 Comparison of the results from HFIS and MCDM.

Comparison criteria		HFIS	MCDM
Strategy Choice	Business as usual	49.7%	55.6%
	Green roofs	28.7%	22.7%
	Rain gardens	21.6%	21.7%
	Replanning	0.0%	0.0%
Overlay area of choosing same strategy (other than BAU)		69.7%	
User-defined decisions		34	141

As discussed in Section 3.2, the two methods produced similar results regarding the total area of each strategy (see table 3.4). The HFIS suggested a bit more rain tank/green roof uptake instead of business as usual (6%). In regard to the spatial distribution of the strategies, 69.7% of the resort planning generated by the HFIS uses the exact same strategy as that used by MCDM. When only looking into polygons with green roof and rain garden strategies, the two methods suggested difference with respect to 3.26% of the planning area. This indicates that there are more conflicts between the two method on the choice of whether to build decentralized systems (from business as usual to green roofs), rather than the size of decentralized systems (green roofs or raingardens)

3.4 Conclusions

In this chapter, a practical decision support method, the Hierarchical Fuzzy Decision-Making (HFDM), was proposed and tested against traditional Multi Criteria Decision-Making method (MCDM). When dealing with inadequate amount of data in the planning process, the proposed fuzzification of GIS system, together with the application of hierarchical fuzzy inference system, could provide more reliable information of the planning area. The method sharply reduces the number of user-defined parameter, which tries to minimize the uncertainty of basic data and user subjective factors in planning decisions. The main results are as follows:

(1) A fuzzy pre-processing and de-fuzzy evaluation methods of GIS layers are proposed, so that the spatial units (such as buildings) that are normally independently evaluated can include comprehensive information of adjacent environments and improve the rationality of planning decisions. According to the median area and area distribution of spatial units in existing GIS, a grid with an area of 1 hectare was determined for fuzzy processing. The results show that the fuzzy process can maintain the dominant characteristics of spatial units, take into account the adjacent environmental parameters and make reasonable adjustments to express important hidden information. This process can also effectively adapt to the hierarchical fuzzy inference system and more realistically simulate the planning process of planners, providing a higher reliability of decision-making assistance.

(2) A hierarchical fuzzy inference system was designed by imitating the planning process of planners. Both the HFDM and the common MCDM were applied to the same planning case. The results show that in the case of similar results, the traditional MCDM method needs to analyze 25 judgment matrices, including 141 subjective comparisons, and requires the users to have high professional quality. While the HFDM only needs 59 reasoning rules, which requires the users to have general professional quality. The design idea of the HFDM proposed in this study reduces the custom parameters by 58%

compared with the conventional method, which reduces the subjective uncertainty of users to a certain extent.

(3) Results indicate that the HFDM proposed in this study and the traditional MCDM can generate similar WSUD planning scheme. In terms of the spatial distribution of applicable technologies, the matching degree can reach 69.7% (excluding regions applying “business as ususal”); The difference in the percentage of applicable technologies is only 6 per cent. The HFDM appealed to evaluate more vulnerable areas through GIS fuzzification, thus more WSUD facilities were recommended, where the MCDM recommended “business as usual”. Considering the robustness of urban water system, a reasonable redundant system is necessary.

3.5 Reference

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Chapter 4.

WSUD-dependent drainage system design

4.1 Introduction

Although there has been a continuous upsurge in developing decentralized systems, the reliable functioning of essential infrastructures such as stormwater drainage is particularly important to prevent urban flooding. The design of urban stormwater drainage networks involves many factors such as the land use and topography of the catchment, which makes it difficult to ensure the optimum of the designed network by manual calculation. Meanwhile, due to the synchronization of pipe network construction and urban development, it is often impossible to predict future development when designing pipe network. As a result, the design of urban drainage systems is increasingly referring to numerical modelling approaches (Korving & Clemens, 2005).

Existing approaches which deal with the generation of sewer network (models) cover various aspects in a different manner. Three aspects can be identified as most relevant (Blumensaat, Wolfram, & Krebs, 2011): (1) topological issues of network generation, (2) hydraulic network dimensioning, and (3) the differentiation of surface characteristics and linkage to the drainage network. In most cases, these approaches were designing drainage networks through topological measures on the basis of DEM data, and validated through hydraulic modelling (Jana, Reshmidevi, Arun, & Eldho, 2007; Liu & Zhang, 2010; Moderl, Butler, & Rauch, 2009; Yan, Tang, & Pilesjö, 2018).

Although these algorithms have been proved to be efficient, there is still a large gap when applying to the long-term planning: The construction of drainage system could affect the planning of other flood prevention facilities, (e.g. less WSUD systems is needed in the areas with newly-build drainage system while more in areas with old systems); Similarly, the planning of WSUD systems will affect planning of the drainage networks (retrofit plans of old urban drainage system might be replaced by sufficient WSUD plans). There are currently no computational tools that simulates the interdependency between two or more facility options.

In this chapter, a WSUD-dependent urban drainage planning method is proposed enabling co-planning between centralized and decentralized systems in the long-term. The method was developed on the basis of urban spatial vulnerability assessment method proposed in chapter 3, encouraging network expansion to more vulnerable areas (according to other plans such as WSUD). The method also evaluates the feasibility and cost-efficiency of the expansion (mainly on depth of pipes in this study), which generates feedback to other plans (WSUD) in the long-term.

4.2 Methods and Data Description

4.2.1 WSUD-dependent drainage system design

The WSUD-dependent planning method is divided into two parts: exploration & expansion module and pipe diameter adjustment module.

The exploration & expansion module is shown in Figure 4.2.1, whereas the flow chart of the proposed algorithm is shown in Figure 4.2.2.

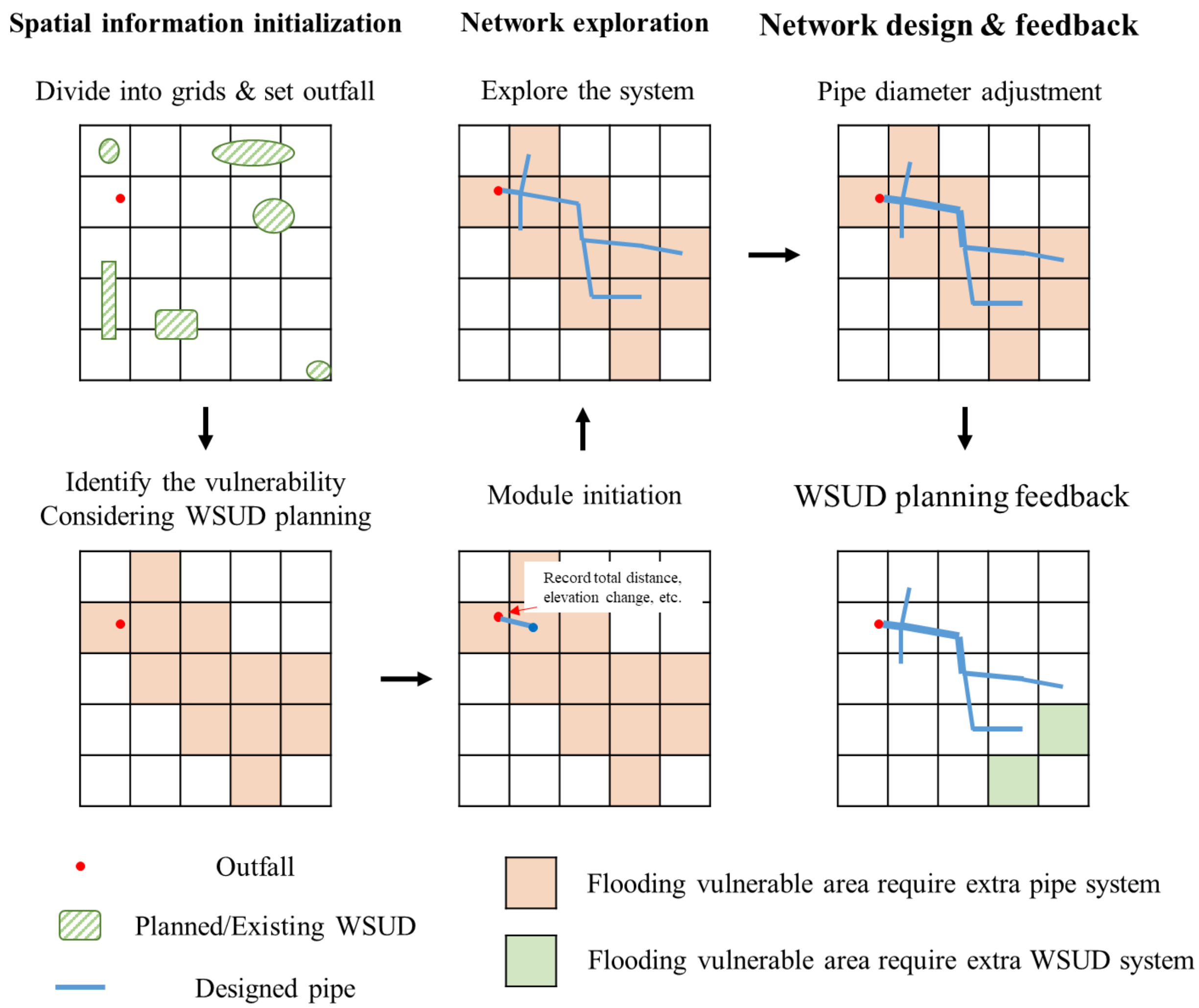


Figure 4.2.1 Exploratory expansion process of the WSUD-depend method

The planning steps are as follows:

1) Spatial information initialization.

The planning area is first divided into grids and the flood vulnerability is evaluated with the fuzzy method presented in chapter 3. In this case study, as the vulnerability of the area now is significantly different to that in the past (when the drainage network was designed), it is hypothesis that all the area (grids) reached by the real network now is vulnerable at the time it was designed and the proposed method would generate a network based on this vulnerable map to enable rational comparison.

The resolution of grid is the same as that in chapter 3. A grid of 100 meters ×100 meters (1 hectare) is adopted to ensure the accuracy while considering the surrounding influence of the structures or plots.

2) Network exploration

Select one or several existing outlets, new outlets, or existing pipe junctions as the initial nodes, take the grid where the initial node locates as the initial grid and expand the network to the four adjacent grids. If the target grid is flood vulnerable and no pipe network is connected in the grid, a new node will be added and connected to the initial node. If the grid is not vulnerable and there is no network connection, a new virtual node is created, and the node is virtually connected to the initial node. If the grid has an established network, then skip.

When setting the upstream node, the location is chosen near the grid centre and adjacent to the roads. When there is no road, the location is selected near the grid centre with no buildings on it. The ground elevation is recorded at the same time when the node is placed. When setting up the connection, the distance between upstream node and the downstream (initial) nodes is evaluated, and the elevation of the pipeline is calculated according to the pipe network slope (considering the covering soil thickness);

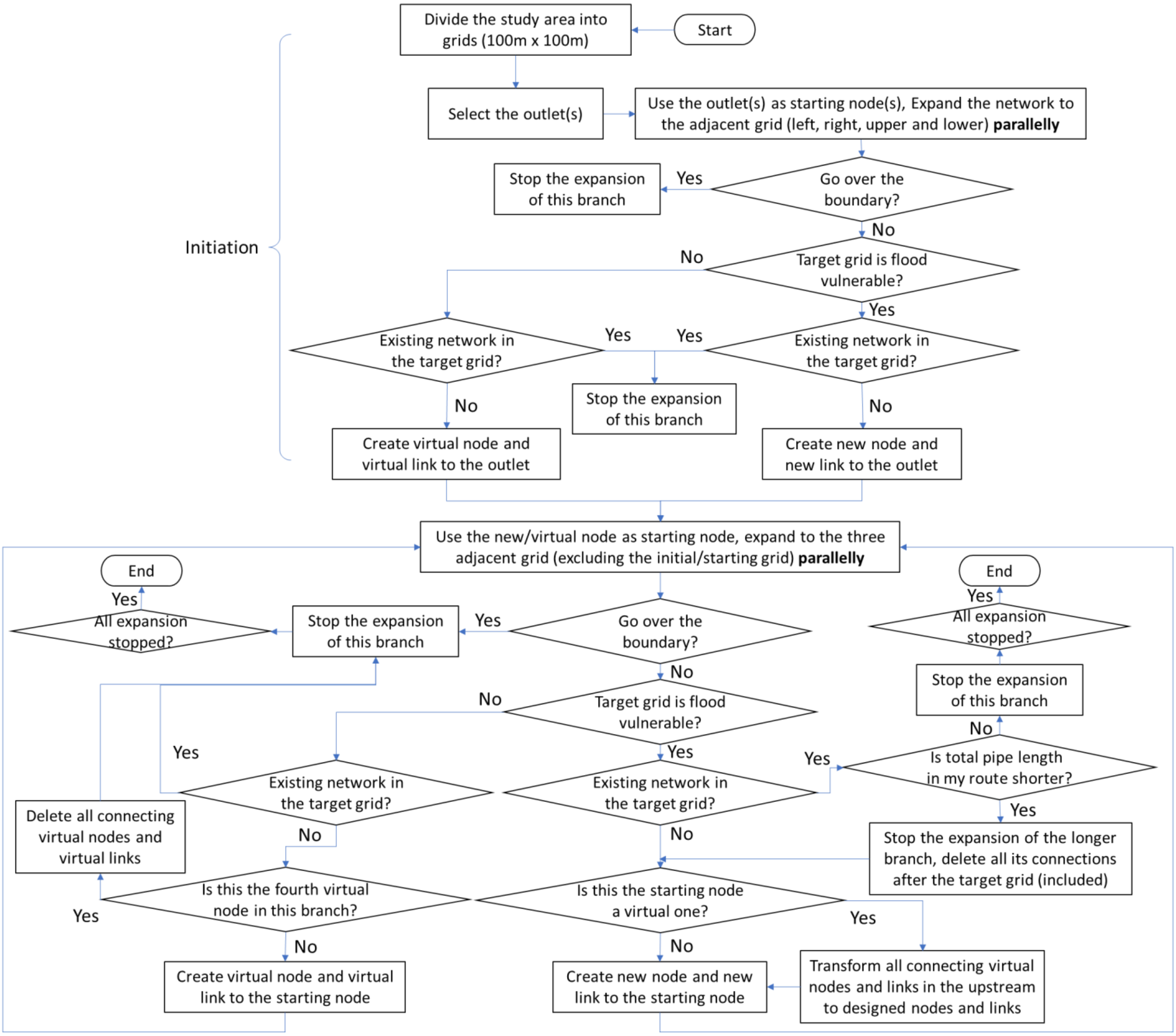


Figure 4.2.2 Flow chart of the drainage system design algorithm

The upstream nodes and upstream virtual nodes are used as the new starting nodes, and the grid where they are located is used as the starting grid. The exploration is carried out to the three adjacent grids (excluding the initial/starting grid explored in the previous step).

If the target grid is flood vulnerable and no pipe network is connected in the grid, a new node will be added and connected to the initial node. If the grid is not vulnerable and there is no network connection, a new virtual node is created, and the node is virtually connected to the initial node. When establishing the connection, record the distance and elevation (for both the bottom and top of the pipe, and the surface) difference between this node and the starting node, and accumulate the distance in the previous step to get the distance between this node and the initial node;

When the explored grid is vulnerable and is connected with planned networks, the distance between the two routes from the initial nodes is compared and the shorter one is retained; the depth from the surface to the top of the pipe was also considered as the second determinant. If there are more than 3 continuous virtual nodes during the exploration and no new nodes are created, the nodes and connections on the exploration path will be deleted. When a new node can be created in the exploring grid and the starting grid is a virtual node, the virtual node of the exploring path will be converted to a node and the virtual path to a path.

3) Network design and feedback

When the exploration is completed (when all explorations reach the planned boundary), the time-area Method (Ross, 1921) is used to calculate the pipe diameter segment by segment in reverse order of the exploration.

As the existing network is designed based on a one in five year standard, the simulated network was also sized under an one in five year return period. Besides, the simulated network was also sized under one in one year and one in two year return period to investigate the possibility of having better system performance with low design standard (less investment or retrofit work) and good topologic structure.

For the grid with high vulnerability but no planned network, the decision maker could consider extra decentralized planning (such as WSUD) in the long-term.

4.2.2 Network evaluation

4.2.2.1 Topological comparison

The topology of the pipe network was evaluated using Graph theoretical approach (Bondy & Murty, 1976), which is a method from discrete mathematics. This method uses mathematical structure to simulate the relationship between points and lines in a network structure. In this chapter, an open source software Gephi (Bastian, Heymann, & Jacomy, 2009) is adopted to calculate the following parameters are compare the structural differences between simulated and real networks:

1) Degree Distribution

"Degree" refers to the number of nodes connected with a certain node through both ends of a pipe network structure, while "degree distribution" refers to the probability/frequency distribution of "degree" of all nodes in a network. The higher the degree of node, the stronger its role in the connection of the network.

2) Modularity

Modularity refers to the degree to which the pipe network can be divided into modules (clustering), which reflects the aggregation of pipes in the drainage system. The higher the modularity, the denser the connections between the nodes in each module, while the connections between the nodes in different modules are more separate (that is, the partition of the pipe network is more significant).

3) Betweenness Centrality Distribution

When the rainwater pipe network system is considered as a whole, there is a shortest path between each upstream inflow node and each outlet (the shortest in structure, not exactly in geography). Betweenness centrality refers to the number of shortest paths through a node in a pipe network system. The higher betweenness centrality the node is, the more important it is to the pipe network.

4) Eccentricity Distribution

Eccentricity refers to the maximum distance between one node and all other nodes. The higher the eccentricity of a node, the greater the delay of its transmission affected by or on other nodes.

The drainage network has obvious directivity under normal working condition. The practical significance of the first two parameters is the connectivity of pipe network and the significance of sub-system structure partition. The latter two parameters is the mutual connection and influence between pipe network nodes/segments and surrounding nodes/segments when flood occurs, so the calculation is based on undirected network.

4.2.2.1 Performance Comparison

The performance of pipe network is evaluated by its hydraulic performance. SWMM was used to connect each grid to the nearest node to form a water catchment system. The following parameters are calculated under three different rainfall conditions to compare the performance difference between simulated network and real network:

1) Total water volume of flooding and maximum overflow flow at a single node;

2) Distribution of flooded time and average overflow intensity of nodes (overflow volume/flooded time);

3) Estimated construction cost.

4.2.3 Site Description

The drainage system in Elster Creek catchment, Australia was selected as the study area in this chapter to apply the proposed method and compare the pros and cons between the modelled network and the real one.

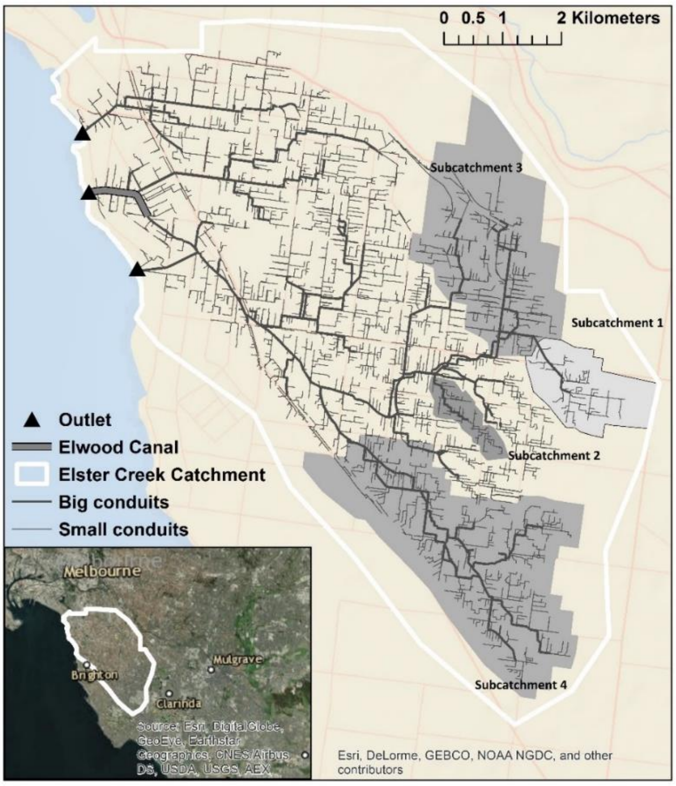


Figure 4.2.3 Existing stormwater network layout plan of Elster Creek (Olesen, Löwe, & Arnbjerg-Nielsen, 2017)

The Elster Creek catchment is located in Melbourne, Australia, which covers an area of approximately 45 square kilometers. This catchment is mainly composed of residential areas, which have suffered multiple flood disasters in recent years (Olesen et al., 2017). The existing drainage network in this area is shown in Figure 4.2.3.

4.3 Results and Discussion

4.3.1 Topologic similarity

The structure of the real network (left) and the simulated network (right, one in two years standard) of Elster Creek watershed is shown in figure 4.3.1.

For the simulated pipe network, the range of the designed pipes was limited to pipes larger than DN300 for the following reasons: 1) the purpose of the simulated pipe network is mainly to guide the overall planning of the pipe network and the collaborative planning with decentralized facilities, too detailed designs could lead to more possibilities and deviations which is a drawback to planners ; 2) smaller pipes are more likely to be the user-end systems which have limited individual impacts on the failure of the overall system, the accumulation impact of them could still be simulated as these catchment areas are still connected to their downstream main pipes. Thus, only pipes larger than DN300 were considered for both systems to enable to comparison.

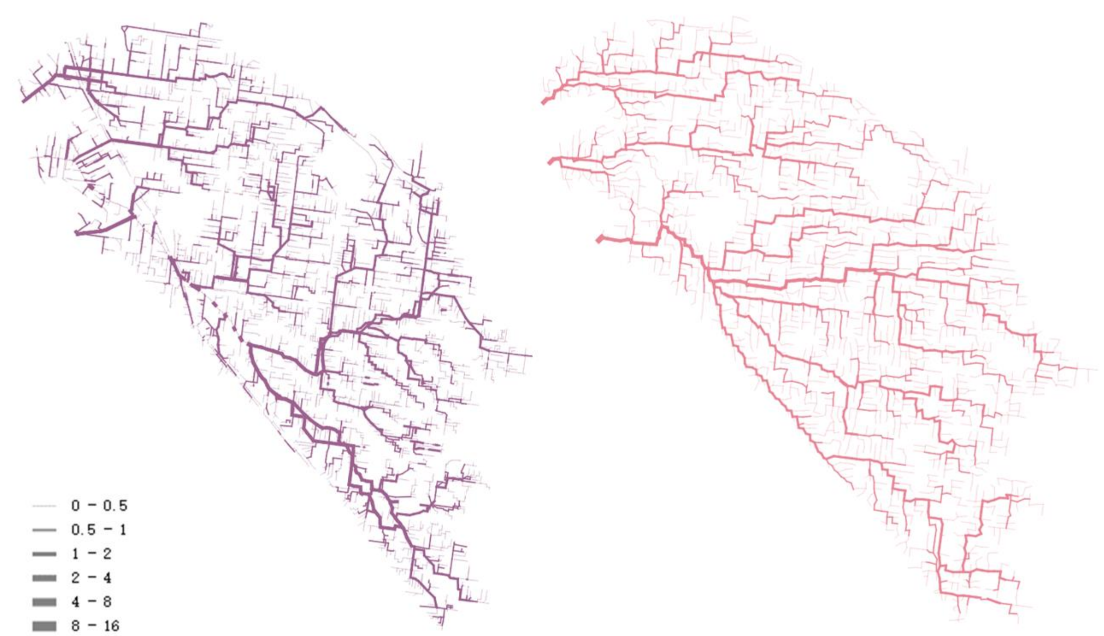


Figure 4.3.1 Existing pipe network (left) and simulated pipe network (right) in Elster Creek

Under this premise, the real network consists of 10,011 nodes and 10,414 pipes. The simulated pipe network consists of 3,330 nodes and 3,360 pipes. In practice, the urban drainage system requires placing manholes at a certain distance, e.g. every of 80 to 100D (nominal internal diameter) with 200m as the maximum in Melbourne. Thus, the existing pipe network has a manhole distancing of 24m – 200m while the simulated pipe network has that of 100m - 140m (according to the size of the grid 100m x 100m), which results in the huge difference of node and pipe numbers. Although the total numbers of nodes and pipes are different, the topological similarity indexes discussed in this section are all evaluated in the form of distribution, so they are still comparable.

It can be seen from figure 4.3.1 that the real network and the simulated network in this basin form three smaller drainage systems according to the three outlet, but separation of the three tree structures in the simulated network is more sharp. In terms of the layout of main pipes (thicker pipe segments), there is no obvious inclination of the north-south main pipes and east-west main pipes in the real network, while the simulated pipe network tends to arrange the main pipes east-west.

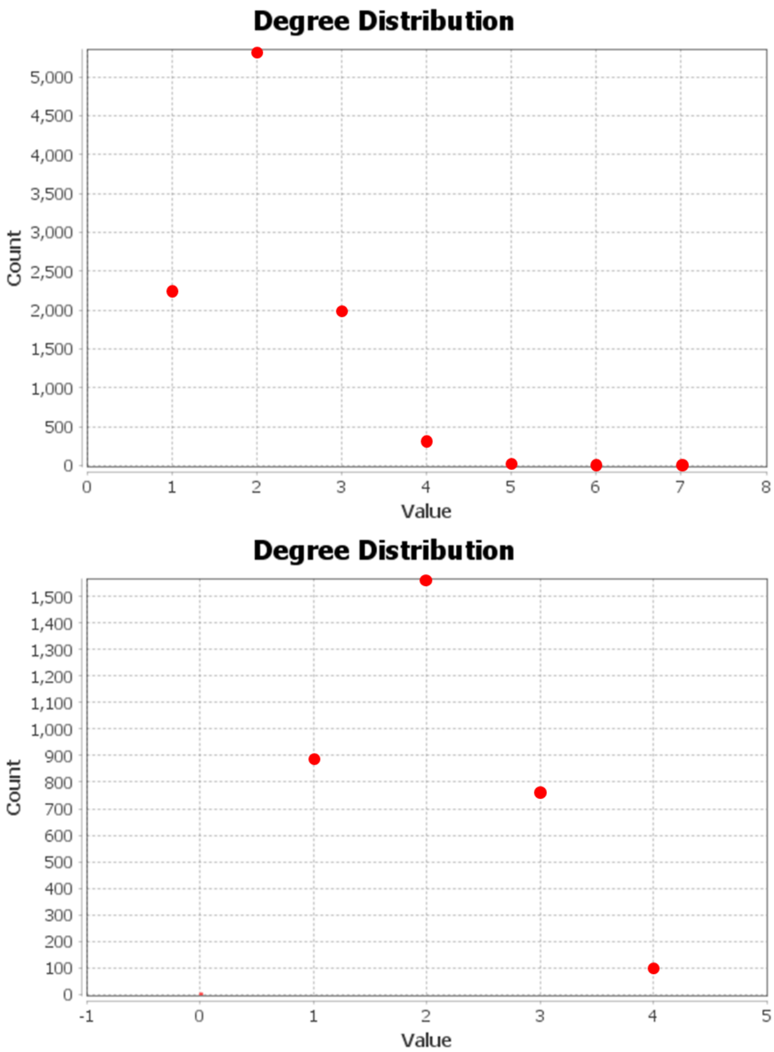
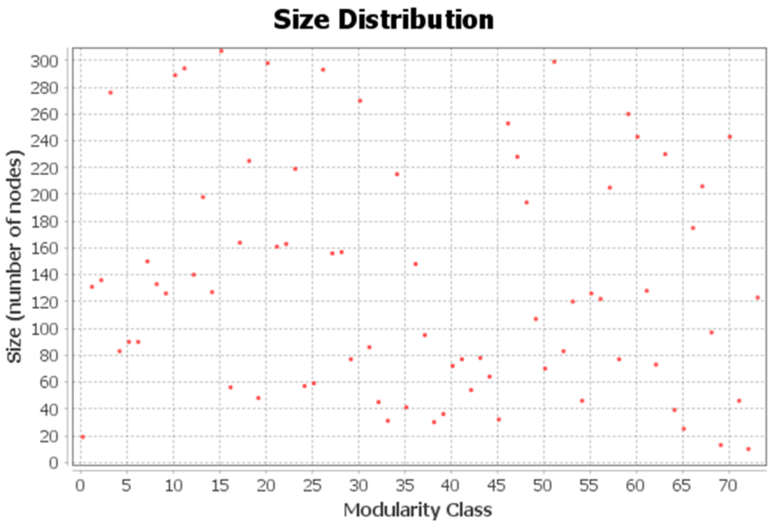


Figure 4.3.2 degree distribution of real pipe network (up) and simulated pipe network (down) in Elster Creek

The average node degree of the real network is 1.029 and the average degree of the simulated network is 1.009. The degree distribution of the two is shown in figure 4.3.2. The results show that the degree distribution of the real network is similar to that of the simulated network. In the two kinds of pipe systems, the node with degree 2 occupies the dominant position, indicating that the node and pipe segment that plays the role of transfer have a large proportion. Compared with the real network, only 1 and 3 nodes in the simulated pipe network account for a slightly higher proportion. This is because in the real pipe network, more stormwater inlet nodes will be arranged along the pipe segment that plays the role of transfer, while only one node will be set in each grid in the simulated network. In the real pipe network, there are nodes with a degree of 5-7, which are often vulnerable parts of the pipe network, but they do not appear in the simulated pipe network.



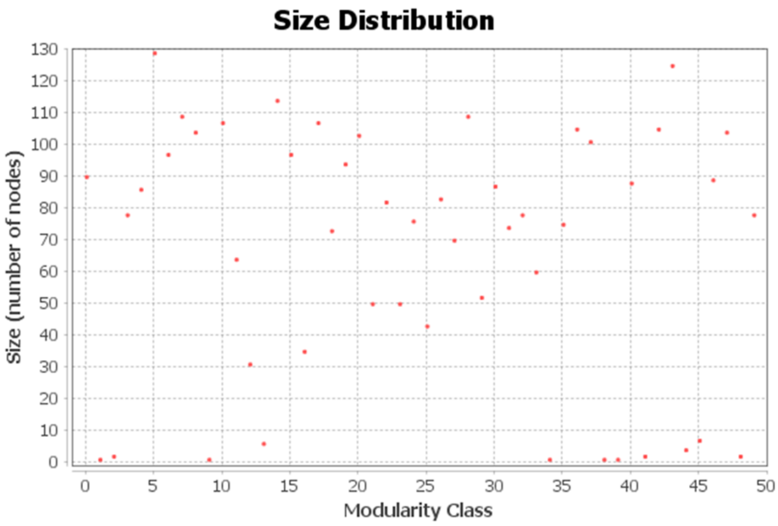
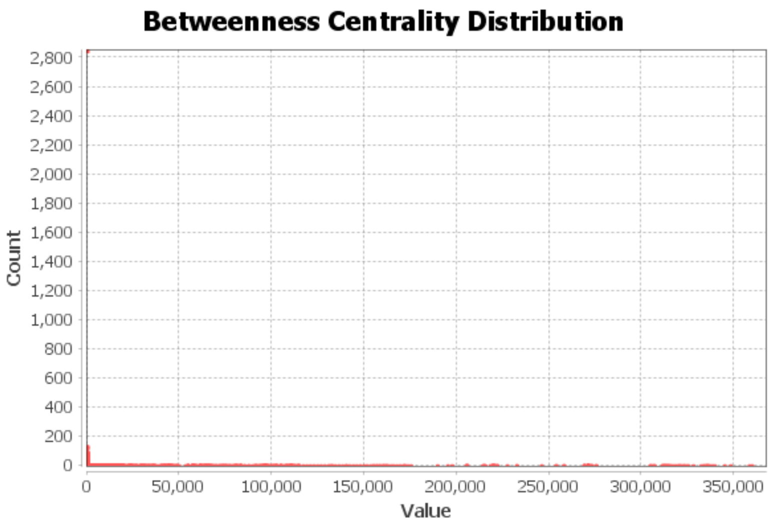


Figure 4.3.3 module size distribution of real pipe network (up) and simulated pipe network (down) in Elster Creek

The modularity of the real network is 0.958 and the number of modules is 74; the modularity of the simulated network is 0.945 and the number of modules is 50. The module size distribution of the two is shown in figure 4.3.3. The Y-axis in the figure is the number of nodes contained in each module. The results show that the real pipe network and the simulated pipe network are clearly divided into modules (with high module degree), and the clustering degree of the regions is similar. The real pipe network module tends to be small but has a large number (samples are concentrated in the lower half of the Y-axis midline), while the simulated pipe network module tends to be large, so the number is slightly small.



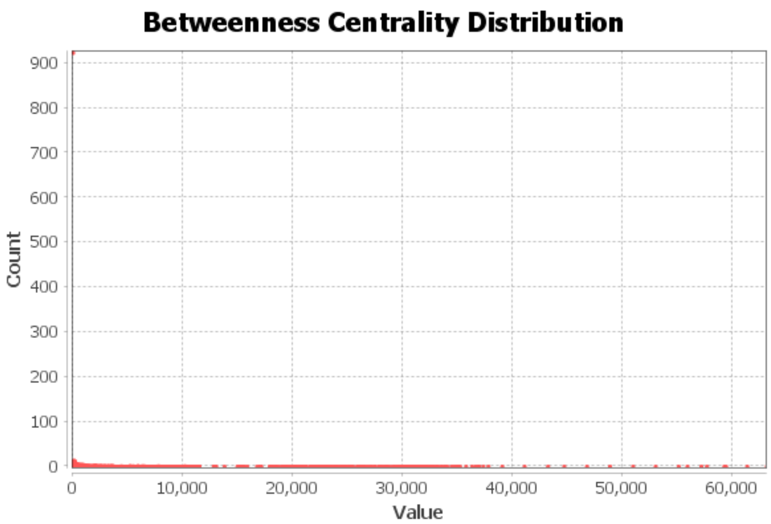


Figure 4.3.4 betweenness centrality distribution between real pipe network (up) and simulated pipe network (down) in Elster Creek watershed

The betweenness centrality distribution of the two is shown in figure 4.3.4, which is roughly the same. There are more nodes with low betweenness and fewer nodes with high betweenness, showing an obvious inverse ratio. The value range of the simulated network is relatively concentrated, mainly below

900,000, while the value range of the real network is slightly wider, mainly aggregates in [0, 700000] and [800000, 1200000]. Therefore, there are extremely important nodes in the real network, which may carry a large amount of transfer flow, and the distribution is uneven.

Figure 4.3.5 Eccentricity distribution of real pipe network (up) and simulated pipe network (down) in Elster Creek

The eccentricity distribution of the two is shown in figure 4.3.5. The overall eccentricity of the real network is higher, which is caused by the fact that there are more nodes and segments of the same length in the network. The eccentricity distribution of real pipe network shows three clear peaks and troughs, while the peaks and troughs of the simulated network are fuzzy. This indicates that there are three independent long-distance drainage pipe chords in the real pipe network, while there are also long-distance drainage pipe network chords in the simulated network, but their independence is not strong, that is, on the whole, the simulated pipe network is less prone to pulse flood peak.

To sum up, the simulated network has certain similarity with the existing pipe network in topological structure, and the design of the simulated pipe network is more uniform, which can avoid the problems of too high node betweenness (too high transfer flow) or too strong eccentricity (pulse flood peak).

4.3.2 Hydrologic similarity

The node overflow volume distribution of the two networks is shown in figure 4.3.6. The distribution of the one in five years simulated network is close to the real network. Compared with the one-year standard and two-year network, the real one and the five-year one accounts for more smaller flooding events, 85.44% and 86.43% respectively. In the real system, 5 nodes had overflow of more than 10m^3, and one node had overflow of more than 100m^3. However, only one and two nodes of the one-year standard and two-year standard simulated pipe network overflow flow is higher than 10m^3, while the five-year standard controls the overflow flow of all nodes below 10m^3. Results show that the existing network can offer sufficient system resilience in a five years storm while having several fragile nodes with extreme floods. Meanwhile the simulated network could significantly reduce the opportunity of having vulnerable layouts due to its explorative design pattern.

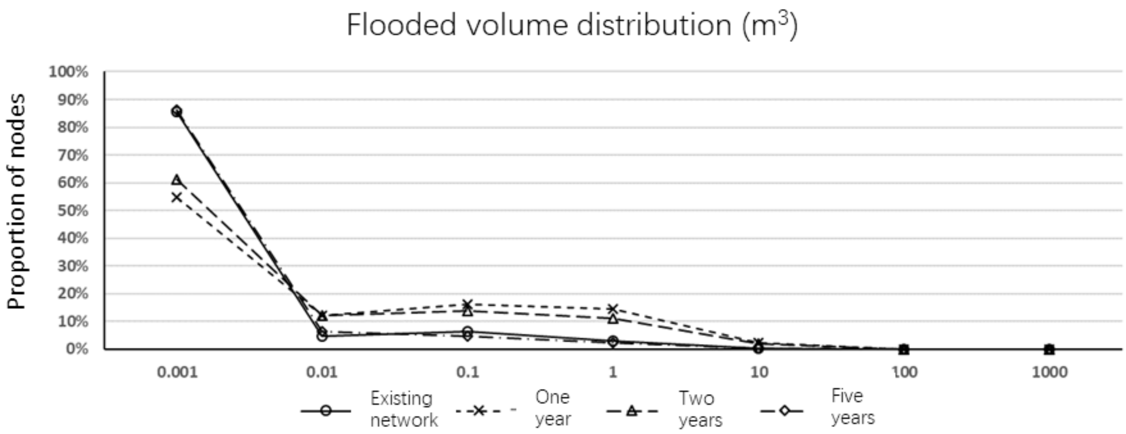


Figure 4.3.6 Flood volume distribution of real pipe network and simulated pipe network in Elster Creek

The distribution of flooded time between real and simulated networks is shown in FIG. 4.3.7. Although different degrees of flood occurred in the four kinds of pipe networks in a five-year storm, 99% of the impacted nodes were flooded for around 1.0 hours. The maximum flooded time of the real network is 4.0 hours, while that of the simulated network is 2.5-3.0 hours. The flood affected nodes of five-year standard simulated network were the least (22.88%), followed by the real network (44.74%), and there were more flood affected nodes of the one-year standard and the two-year standard (66.46% and 59.49%).

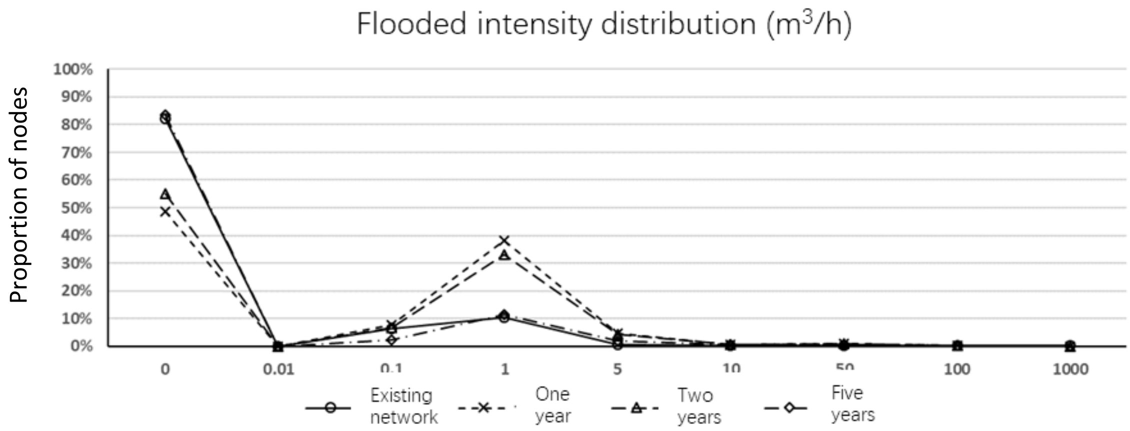


Figure 4.3.7 Flood intensity distribution of real pipe network and simulated pipe network in Elster Creek

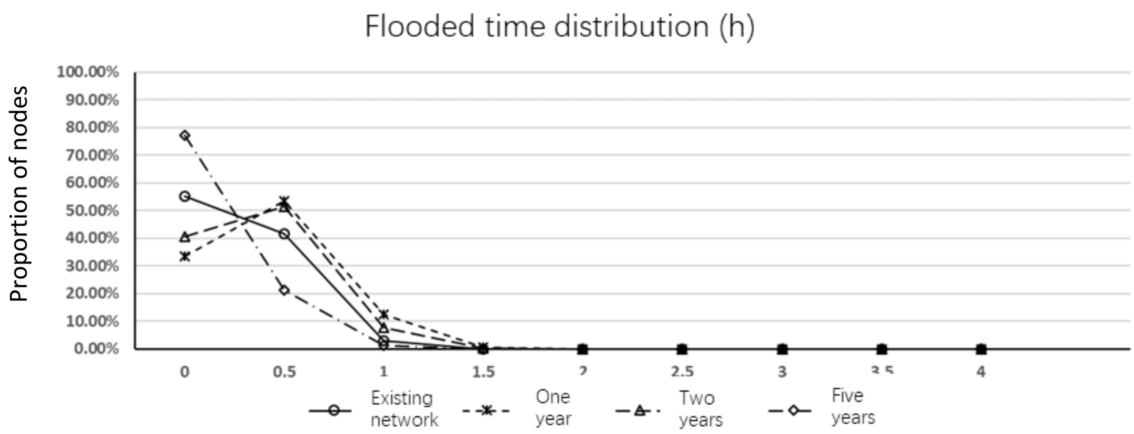


Figure 4.3.8 Flood time distribution of real pipe network and simulated pipe network in Elster Creek

The flooding intensity distribution can be obtained by considering the overflow volume and flooded time of impacted nodes, as shown in FIG. 4.3.8. The proportion of flood affected nodes of the one-year standard and two-year standard simulated network with low intensity (less than 1m^3/h) is much higher than the existing network and the five-year standard simulated network, but there are 11 nodes in the existing network with flooding intensity higher than 100m^3/h.

Table 4.3.1 Comparison of the hydraulic performance

	Total flooded volume （m^3）	Max node flooded volume （m^3）	Construction cost	Short flood event ratio (<30min)
Existing network	558.295	302.073	1.0000	96.89%
One year return period	410.570	18.168	0.7206	86.88%
Two years return period	310.616	15.850	0.7999	91.80%
Five years return period	47.927	2.528	1.0935	98.47%

Table 4.3.1 shows the total overflow flow volume, maximum node overflow volume, total construction cost (calculated by pipe diameter and pipe length) and short-term flooding ratio (for nodes with flood duration less than 30 minutes) of the four pipe networks.

The above comparison results show that the five-year simulated network has similar performance of the real network. However, there are several vulnerable points in the real system, which leads to higher total flooding volume and the maximum node overflow volume than all the simulated pipe networks. Such difference was resulting from the dual optimization on the layout and sizing, while the real network, as a result of cumulative upgrades, usually optimize one at a time.

With the urban vulnerability analysis method from chapter 3, the WSUD-dependent drainage system design algorithm can reasonably plan urban drainage network and adjust pipe diameters. Plans under one in one year or one in two years standard have slightly lower performance than the existing pipeline system, but these networks are less easily to include vulnerable node, therefore does not lead to serious flooding in the area. Meanwhile, the total construction cost is less than 80% of the existing network.

The simulation network under one in five year standard has excellent hydrological performance, and its construction cost is only 10% higher than the existing pipe network.

4.3.3 Robustness of the networks

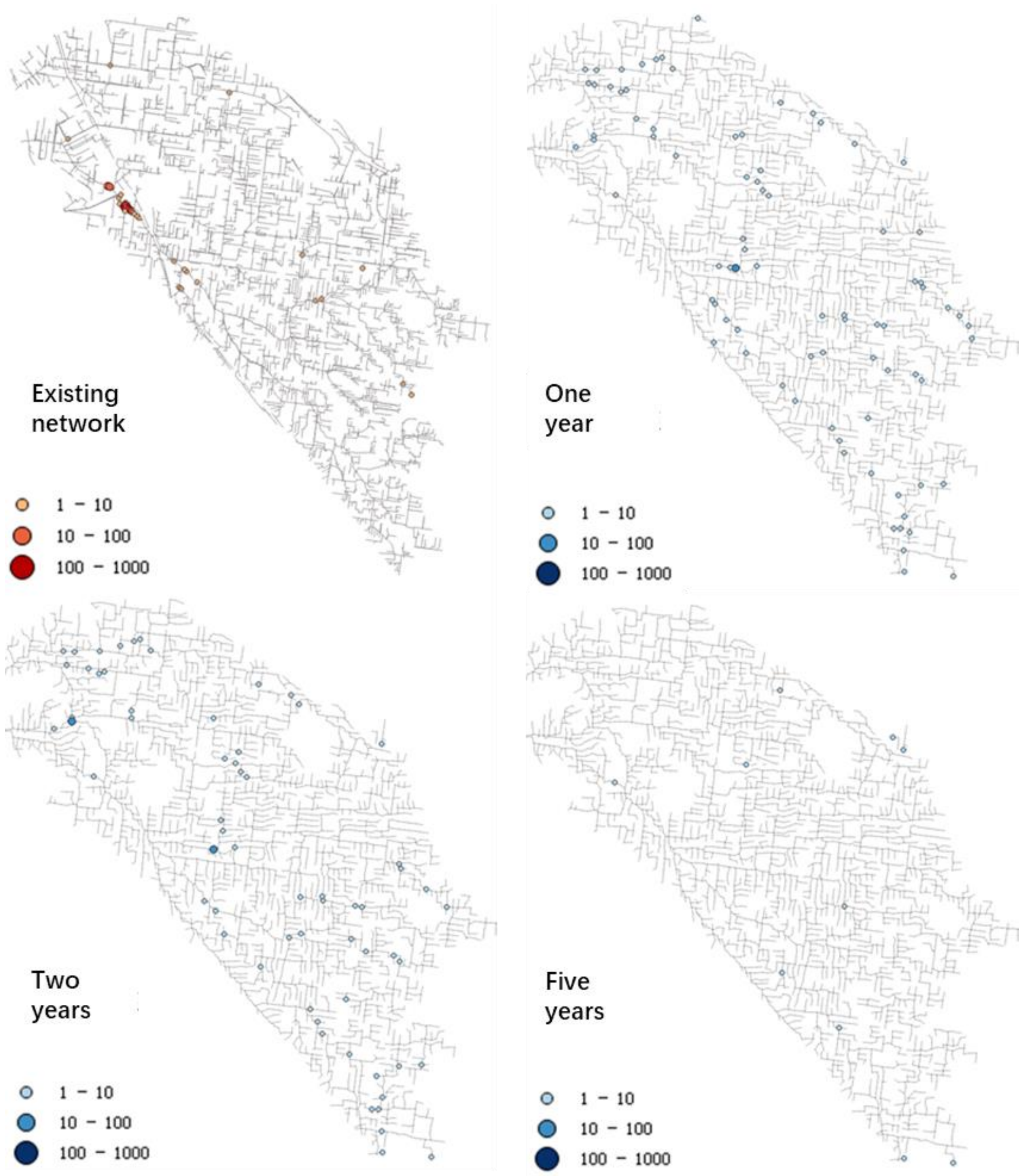


Figure 4.3.9 The vulnerable points of real pipe network and simulated pipe network in Elster Creek

The distribution of vulnerable nodes between the real and simulated pipe network with different standards is shown in figure 4.3.9. As the five-year designed network is more efficient and more expensive than the existing network, it will not be discussed in this section.

As can be seen from the figure, although the one-year and two-year designed network has more flooded nodes than the existing system, its node overflow volume is smaller and more dispersed. However, the overflow node of existing pipe network is more concentrated, and the overflow volume is extremely large.

As the damage of urban flooding is often a process from quantitative change to qualitative change. Minor flood only brings inconvenience to the life of residents, while large flood could lead to a disaster, causing loss of life and property. Therefore, for the robustness of urban drainage network, the impact of small and scattered overflow on the city is far less than that of large and concentrated overflow. Therefore, the proposed planning method can effectively improve the robustness of the city.

4.4 Conclusion

In this section, a WSUD-dependent drainage system planning method was proposed which is applicable to old and new area network extension planning of for urban stormwater network planning. On the basis of the fuzzy evaluation method in chapter 3, the vulnerable areas were identified and the planned drainage system be expanded these areas and being optimized. Main conclusions are as follows:

1) On the basis of the real planning process and objectives of existing drainage network, the simulated network generated by the proposed method can well reproduce the degree distribution (connectivity) of existing network, while avoiding the occurrence of over-high-degree nodes (fragile nodes); It has the same modularity (partition sharpness), but the clusters are larger and lesser than the real one. The distribution of betweenness centrality (node importance) is roughly the same, but the occurrence of nodes with too high importance (fragile nodes) is avoided. Compared with the real network, the eccentricity

(long-distance drainage) is lower and more concentrated, and the pulse flood peak is less easy to occur.

2) The performance of the one-in-five years designed network is generally similar to that of the real network (distribution of overflow volume, node flooded time, node flooding intensity, etc.), and is better than the one-in-one year and one-in-two years designed network. However, there are several vulnerable nodes in the real network, and the maximum overflow volume, maximum flooding intensity and total overflow volume of the nodes are much higher than all the simulated networks. Plans under one in one year or one in two years standard have slightly lower performance than the existing pipeline system, but these networks are less easily to include vulnerable node and the total construction cost is less than 80% of the existing network. The simulation network under one-in-five-year standard has excellent hydrological performance, and its construction cost is only 10% higher than the existing pipe network.

3) The lower standard network generated by the proposed algorithm has more flood affected nodes with smaller more dispersed overflow. Compared with the larger and more concentrated flood affected nodes of the real network, the simulated network systems can also better inhibit the transformation of flood disaster from quantitative change to qualitative change under the lower design standards, improve the robustness of the city, and reduce the construction cost of the network.

4.5 Reference

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Chapter 5.

Urban water infrastructure

implementation pathway

5.1 Introduction

Although the idea of infrastructure long-term planning has been proposed for several decades, the long-term implementation and performance of infrastructures are often affected by future uncertainties, including urban economy, climate and population changes. These parameters are extremely difficult to predict due to long term uncertainties. The most convincible case is the "shrinking city" phenomenon in Dresden, Germany. As the capital of the Saxony state, the second largest city in eastern Germany, experts believed the economy, population will get rapid development after the unification in 1990. Large-scale construction of infrastructures was carried out to serve the rapid development. But in a few years, Dresden’s population was shrinking rather than growing, its demand for water was sharply reduced, and the water system facilities that the government planned and invested in for a long time did not promote the city's development but became a drag. In order to minimize losses, Dresden predicted the future population trend for seven times in the following 15 years and revised the urban planning, but none of the predictions was correct (Moss, 2008; Wiechmann & Pallagst, 2012). It is not just Dresden but many cities in Germany and Europe face the same problem.

In order to deal with this problem, more and more computational tools have been developed in aiding future scenarios exploration to reduce the impact of future uncertainties, as well as to assist the design of more reliable long-term planning, such as the Adaptation Tipping Point (Kwadijk et al., 2010), Robust Decision Making (Lempert, Groves, Popper, & Bankes, 2006), Information gap (Ben-Haim, 2006) and so on. There are also some exploratory planning tools that try to simulate the performance of different infrastructure plans under different scenarios, so as to further reduce the influence of subjective knowledge limitations of planners. For example, Adaptive Policy Making (Walker, Rahman, & Cave, 2001), Adaptation Pathways (Haasnoot, Middelkoop, Offermans, Beek, & Deursen, 2012) and Dynamic Adaptive Policy Pathway (Haasnoot, Kwakkel, Walker, & ter Maat, 2013).

As stated in the literature review section, the limitations of existing tools are that they cannot assess the adaptability of complex real-world water systems with multiple technologies (centralized + decentralized), nor can they optimize water systems for multiple design objectives simultaneously. As an extremely large number of future scenarios need to be explored and tremendous amount of possible urban water system plans need to be evaluated, the calculation time is extremely large. These methods all choose to optimize the calculation efficiency by exploring in specific schemes (future scenarios and/or urban water system plans which likely to have better performances). This optimization method has the following disadvantages:

1. Due to the limitation of the exploration scope, the optimal planning scheme obtained may be the local optimal rather than the global optimal, so the final proposed scheme is not necessarily the best one;

2. Due to the narrowing of the scope of exploration, there is no continuity between better schemes, no transition between schemes, and poor adaptability of planning;

3. In the optimization of the planning scheme with multiple design objectives, the exploration scope will be limited to a very small extent, and it is very likely that the optimal scheme satisfying multiple objectives can't be found at the same time. Therefore, this method is often not used for multi-objective planning.

Therefore, a new exploration method was proposed in this chapter which explores, evaluates, analyzes and designs transition of urban water system planning with global exploration, and accelerates the calculation process through machine learning (see chapter 6 and chapter 7 for details), so as to avoid the above shortcomings.

In this chapter, an optimal plan and transition design method of water system through global scenario exploration is proposed to improve the adaptability and robustness of long-term urban water system planning. Starting from the current state of the city, all reasonable urban development situation at each time step (climate, population, economy, etc.) were explored as well as possible urban water system construction (construction of WSUD facilities, expansion pipe network, etc.). By evaluating the efficiency of water systems in all possible urban scenarios in a certain time step, the robustness of the system planning was analysed, and the transition routes between schemes were designed. The rationality of the model inputs was also evaluated through a sensitivity analysis to eliminate redundant parameters and their uncertainties to the resulting pathways.

5.2 Methods and Data Description

5.2.1 Multi-strategy exploration and evaluation module

In this section, a multi-strategy scenario exploration module is proposed and developed on the basis of DAnCE4Water platform (C. Urich & Rauch, 2014; Christian Urich et al., 2012).

DAnCE4Water, Dynamic Adaptation for enabling City Evolution for Water, is a decision-making tool that integrates urban development simulation, water system hydraulic calculation (SWMM) and cloud computing. As one of the core functions of the platform, Urban Development module (UDM) can simulate the evolution process of a city and its water infrastructure under different development scenarios (climate change and population growth). As a long-term planning and decision-making supporting tool, DAnCE4Water is an improvement of robust decision planning method. Its workflow is shown in figure 5.2.1, and the process is as follows:

1) Input the current status of city C, water system W, city development scenario in the next time step Δ C into UDM, and simulates the city status C' in the next time step;

2) Evaluate the performance of the water system W, deciding the optimized adjustment Δ W, simulates the updated water system W' in the UDM;

3) Re-evaluate the efficiency of the water system and adjust it repeatedly until the efficiency of the water system meets the design goal;

4) Set C' and W' as the current status, and repeat step 1) to 3), to get one optimized urban water infrastructure implementation pathway under city development scenario ΔC;

5) Select a new city development scenario ΔC', repeat the above process.

6) Select the pathway that can satisfy the most development scenarios as the robustness pathway.

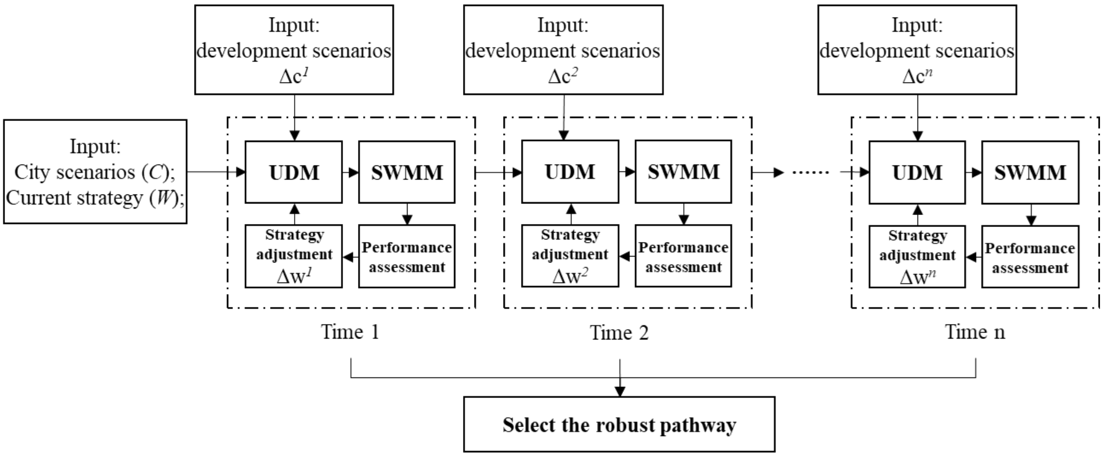


Figure 5.2.1 DAnCE4Water exploration process

Compared to Robust Decision Making (Lempert et al., 2006) and Information gap (Ben-Haim, 2006), this algorithm integrates the timing design of planning schemes and can better provide construction guidance for long-term planning. Compared to Adaptive Policy Making (Walker et al., 2001), Adaptation Pathways (Haasnoot et al., 2012) and Dynamic Adaptive Policy Pathway (Haasnoot et al., 2013). It relies more on exploratory simulation, which is less affected by the subjective cognitive limitations of planners, and can provide guidance for long-term planning with less uncertainty.

However, since this algorithm only uses one single data stream in each exploration process, and can only consider the increase or decrease of the same candidate strategy in one exploration, it cannot be applied to the water system planning considering the common development with multiple strategies in the real world.

Therefore, a multi-strategy exploration module based on the DAnCE4Water platform was developed by reconstructing the exploration process, as shown in figure 5.2.2. The main idea to replace the single data stream with parallel data streams, replace random exploration with global exploration, and separate the evaluation module from the exploration process.

1) Select the current status of city C, water system W, duplicate the data stream according to all possible city development scenario {Δc} , input the data streams into the UDM, and simulate all possible city status {C’} in the next time step

2) For each city status C’ in {C’}, duplicate the data streams according to all possible water system adjustment options {Δw}, input the data streams into UDM, simulate all possible water system status {W’} in C’;

3a) Evaluate the performance of each water system in {W'} under the corresponding city status C ', and store results in the database for further analysis;

3b) Take {C'} and {W'} which matches with each C ' as current status for the next time node, repeat the process to explore all possible urban scenarios and water system.

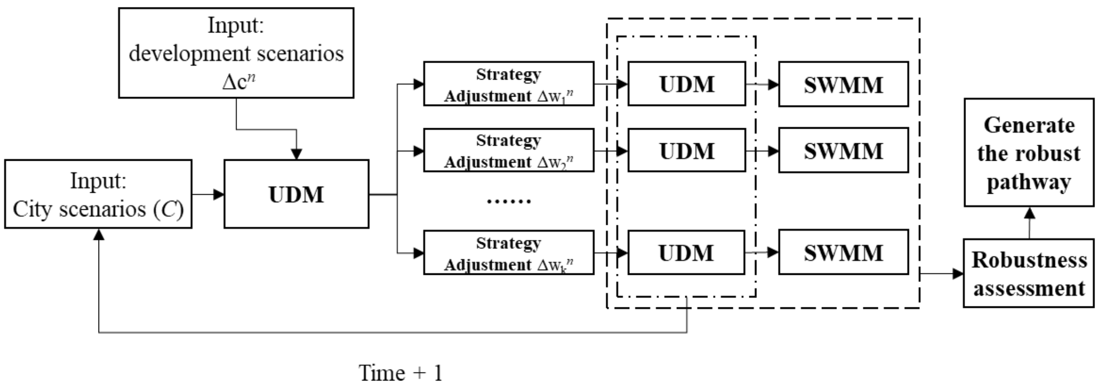


Figure 5.2.2 The proposed multi-strategy exploration and evaluation module

5.2.2 Robustness evaluation module

On the basis of the exploration module, a robustness evaluation module is proposed in this section to evaluate the robustness of different water system schemes in the long-term urban development.

As shown in figure 5.2.2, the robustness evaluation module is independent from the exploration module. The output of the exploration module at each time step is the input of the exploration module for the next time step, as well as the input of the performance evaluation module. Such separation improves the efficiency of both modules. The output from performance evaluation module will serve as the input of the robustness evaluation module in this section.

Robustness is the ability of something to withstand or overcome adverse conditions or to be rigorously tested (Stevenson, 2010). The robustness of urban water infrastructure planning should not only include the robustness of water system, but also ensure a sufficiently low failure rate in the case of foreseeable or unforeseeable flood disasters. It should also include the robustness of planning, that is, the urban water system can be adjusted according to the future or unforeseeable development trend, so as to ensure that the planned water system can always have sufficient robustness. This section discusses the former robustness, i.e. the robustness of water system, the latter one will be discussed in the next section.

Two user-defined parameters, failure assessment matrix (D) and acceptable failure rate (A), are introduced to evaluate the robustness of water system. These two custom parameters are different from the uncertain custom parameters described earlier in this thesis. The former ones are mainly the experience description or guess related to the objective fact, and its uncertainty will lead the deviation of the objective fact in the simulation. The D and A are the planner's description of objective fact. Although different planners have different descriptions of the same fact, it will not affect the objective fact that have happened. This is one of the advantages of separating the robustness evaluation module from the exploration process.

A customized 1×n failure assessment matrix (D) is used to evaluate whether a certain water system W meets the design goal or expectation in a given situation. The elements in the matrix correspond to each performance index of a design goal of the water system, while the planners customize the expectation interval di of each performance index. If the system performance P obtained in step 3a) of 5.2.1 can meet all the expectations of indicators in D, it is considered that the water system has no failure under a given situation. Whether a water system fails in a specific situation can be calculated by equations 5.1 and 5.2.

$$s_i = \begin{cases} 1, & p_i \in d_i \\ 0, & p_i \notin d_i \end{cases} \qquad (5.1)$$

Where,

s_i refers to the success of a certain performance indicator under a give situation;

p_i refers to the ith value of the performance indicator;

d_i refers to corresponding expecting value range of the indicator.

$$F_i = 1 - \prod_{i=1}^{n} s_i \qquad (5.2)$$

Where,

F_i refers to the failure determination of the water system under a given situation;

By comparing to the acceptable failure rate (A), whether the assessed water system can meet the design goal or expectation stably in all possible scenarios could be determined, which reflects the robustness of the water system. For a specific water system W, the ratio of all the failure determination times and all the evaluation times in the exploration process is the failure probability of the system. Acceptable failure rate refers to the maximum failure probability of water system that the city or urban planners are willing to take. Therefore, the robustness of the water system can be calculated by equation 5.3:

$$R_i = \left\lceil A - \frac{\sum_{j=1}^{n} F_j}{n} \right\rceil \qquad (5.3)$$

Where,

R_i refers to the robustness of the *i*th water system scheme

F_j refers to the failure determination of the water system in the *j*th evaluation;

n refers to total number of evaluation times of the water system.

$\lceil x \rceil$ refers to the symbol of ceiling(x).

5.2.3 Adaptability design module

As mentioned above, the robustness of water system long-term implementation is considered, and an adaptation design module is proposed in this section. As shown in figure 5.2.2, the adaptive planning module proposed in this section is only related to the robustness evaluation module, so it can be quickly adjusted according to the adjustment of customized parameters in the robustness evaluation by planners.

Firstly, all water system schemes are classified according to their corresponding time steps. According to the robustness evaluation results, the robust water system schemes in adjacent time steps are connected in series, and then the series path is adjusted through adaptivity assessment. The adaptability of each scheme is determined by equations 5.4 and 5.5.

$$C_{W_{t,i},W_{t+1,j}} = \begin{cases} 1, & \frac{\left|W_{t+1,j} - W_{t,i}\right|}{\Delta w} \leq 1 \\ 0, & \frac{\left|W_{t+1,j} - W_{t,i}\right|}{\Delta w} > 1 \end{cases} \qquad (5.4)$$

Where,

$C_{W_{t,i},W_{t+1,j}}$ refers to the connectivity between water system $W_{t,I}$ and $W_{t+1,j}$;

$W_{t,i}$ refers to the ith optional water system in time step t;

Δw refers to the maximum construction works that can be built between two adjacent time steps.

$$AD_{W_{t,i},W_{t+1,j}} = C_{W_{t,i},W_{t+1,j}} R_{t,i} R_{t+1,j} \qquad (5.5)$$

Where,

$AD_{W_{t,i},W_{t+1,j}}$ refers to the adaptivity between water system $W_{t,I}$ and $W_{t+1,j}$;

$R_{t,i}$ refers to the robustness of the ith optional water system in time step t.

Disconnect the path with an adaptability of 0 and delete the planning scheme that is not connected with the node of the previous time step in the order of time, and then the construction path planning diagram of urban water system adaptation pathway can be obtained.

5.2.4 Site Description

The case study was carried out in Scotchman's Creek catchment, locates at the southeast of Melbourne CBD. The catchment is mostly located within Monash City council but a part of the catchment (6%) is situated within Whitehorse City council. It has an area of approximately 10.36 km2 and a population of approximately 25,000 residents.

The council started to introduce rainwater tanks to households since 2005 to deal with the unpredictable rainfall events (e.g., reduce peak flow during highly intensive rainfall event, store stormwater during drought season). Although the council tried to set up a progressive goal of rainwater tank uptake rate in the area, there were several obstacles in making such a plan: (1) The spatial distribution of rainwater tanks will largely influence the flood resistance in the catchment resulting from them. Thus, the promoting of higher rainwater tank uptake rate cannot be easily determined compared to upsizing pipe systems; (2) The population growth in the area could infect the construction of houses and buildings which increases the impervious surfaces in the catchment as well as the opportunity for uptake rainwater tanks; (3) The flood-resistance robustness of the combined drainage system (under different rainwater tank uptake ratio and pipe system capacity) was unclear.

Thus, a long-term (2015–2035) evolution of the urban development, climate change and water infrastructure adaptation were simulated by DAnCE4Water (Dynamic Adaptation for enabling City Evolution for Water) (C. Urich & Rauch, 2014; Christian Urich et al., 2012) to set up a robust plan of progressive goals for both rainwater uptake ratio and drainage pipe system upsizing. With the initial city scenario established based on the real-world catchment in 2015, DAnCE4Water ran in a 5-year interval to simulate the transformation of the city and assess the urban water system performance with different drainage infrastructure updates under all possible development scenarios.

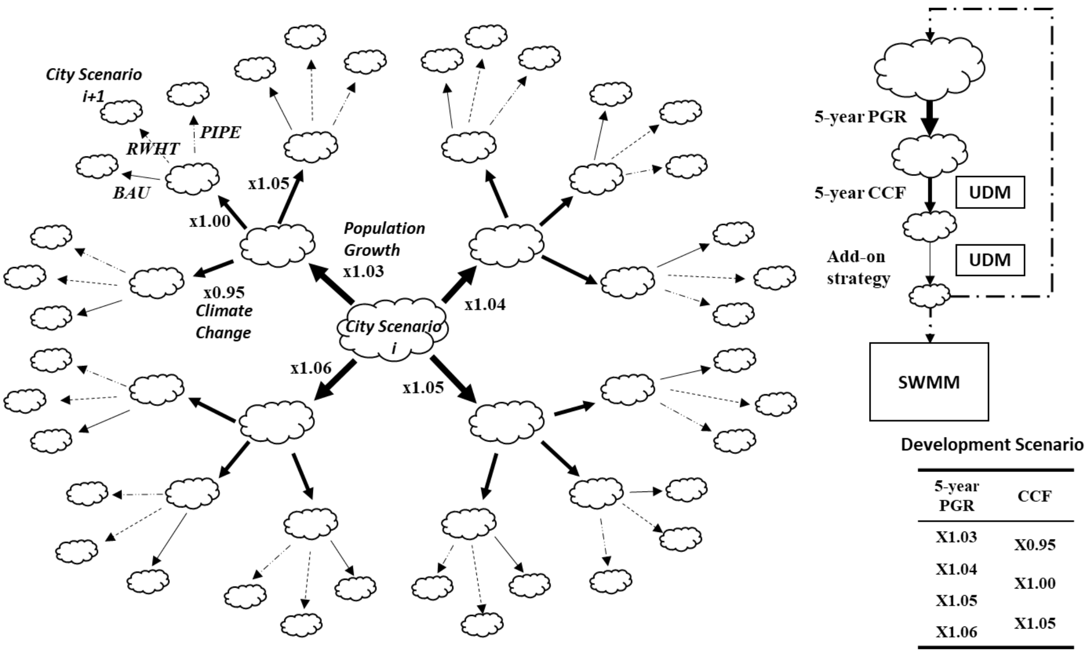


Figure 5.2.3 Designed exploration of the Scotchman's Creek catchment area.

The development scenario consists of two parameters: the population growth rate (PGR) and the climate change factor (CCF). As the population growth does not directly contributes to the change of urban land uses, the household growth rate was derived from the population growth. The growth of household numbers usually leads to the need for new houses and buildings, thus changing the land uses in the urban area. The 5-year household growth rate is between [0.03,0.06] has been which calculated based on the minimum and maximum annual population growth rate in the area according to the 1990–2015 census data from the Australian Bureau of Statistics (see table 5.1).As the annual population growth ranged from 0.009 to 0.022 per year, the 5-year population growth would be 0.046 – 0.114, assuming every two person turns into one household, the 5-year household growth rate was thus set to 0.03 – 0.06. DAnCE4Water would replace old buildings and construct new ones according to the increased household through its urban development module (UDM) (C. Urich & Rauch, 2014; Christian Urich et al., 2012). The 5-year climate change factor is a coefficient used to magnify the 5-year designed storm. Initialized to 1.00, CCF is assumed to change every 5 years within three rates: 0.95X, 1.00X or 1.05X.

Three drainage update options were tested: (1) business as usual, (2) uptake rainwater harvesting tanks and (3) upsize drainage pipes. "Business as usual (BAU)" maintained the existing infrastructures from the previous step. The more

BAU was taken, the less contribution would be done in reducing flooded junctions. “Uptake rainwater harvesting tank (RWHT)” increased the current probability of households installing rainwater harvesting tanks by 5%. The more RWHT was taken, the more decentralized systems would be built to reduce the runoff and peak flow. “Upsize drainage system (PIPE)” upgrades the drainage network, which was divided into 4 groups according to their diameters. Each upgrade enlarged one group of pipes, from the large one to the small one. The more PIPE was taken, the higher capacity of the drainage network would be.

Table 4.1 Population change in Australia (1990 - 2015)

Time	Population	Population growth rate
Dec-1990	17,169,800	-
Dec-1991	17,379,000	1.22%
Dec-1992	17,557,100	1.02%
Dec-1993	17,719,100	0.92%
Dec-1994	17,893,400	0.98%
Dec-1995	18,119,600	1.26%
Dec-1996	18,330,100	1.16%
Dec-1997	18,510,000	0.98%
Dec-1998	18,705,600	1.06%
Dec-1999	18,919,200	1.14%
Dec-2000	19,141,000	1.17%
Dec-2001	19,386,500	1.28%
Dec-2002	19,605,400	1.13%
Dec-2003	19,827,200	1.13%
Dec-2004	20,046,000	1.10%
Dec-2005	20,311,500	1.32%
Dec-2006	20,627,500	1.56%
Dec-2007	21,016,100	1.88%
Dec-2008	21,475,600	2.19%
Dec-2009	21,865,600	1.82%
Dec-2010	22,172,500	1.40%
Dec-2011	22,522,200	1.58%
Dec-2012	22,928,000	1.80%
Dec-2013	23,297,800	1.61%
Dec-2014	23,640,300	1.47%
Dec-2015	23,984,600	1.46%

(source: 3101.0 Australian Demographic Statistics)

The exploration randomly selected a PGR, a CCF and a drainage infrastructure update within the available range and applied to the base city scenario. The UDM would then generate a future scenario of the city while the performance of the combined system (the number of flooded junctions in the catchment area along the drainage network) would be evaluated by SWMM. The result city scenario was saved as the base city scenario for the next 5-year decision (see Figure 5.2.3).

The result scenarios were classified by the drainage infrastructure status (e.g., how many steps of BAU, RWHT and PIPE were adopted respectively). The corresponding distribution of system performance (flooded junctions) for each status was calculated. As only one strategy was taken in each decision step, the status contains the year information as well. If the number of flooded junctions of a status was below the target (110 in 2020, 100 in 2025, 90 in 2030 and 80 in 2035, which is 100%, 91%, 82%, 73% of the flooded junctions in 2015) in over 95% of the cases, the status would be consider “robust.” The “robust” statuses were connected in a timeline to form a drainage infrastructure implementation pathway as the long-term plan in this case study.

5.2.5 Sensitivity Analysis

A Sensitivity analysis of the model is helpful to understand the hidden impact of input changes on output, so as to determine which parameters need higher accuracy or more accurate prediction to ensure more accurate model output. In this section, the sensitivity analysis was carried out for the exploration module only, as the robustness evaluation module and the adaptive planning module are both analysis and processing of the results of the exploration module.

Morris method (Morris, 1991) is a widely-used method in modelling to determine which factors may have effects which are (a) negligible, (b) linear and additive, or (c) nonlinear or involved in interactions with other factors (Saltelli, Tarantola, Campolongo, & Ratto, 2004). Through individually randomized ‘one-factor-at-a-time’ experiments, the impact of changing one factor at a time (the elementary effect) is evaluated in turn.

1) Randomly select the values of each parameter as the initial status;

2) Select one of the unchanged parameters, slightly change its value (not beyond the value range), and record the change of the result (equation 5.6). Repeat this step until all parameters have been changed.

3) repeat step 2) 10 times from the initial status;

4) repeat steps 1) to 3) 50 times and evaluate the sensitivity of the model according to equations 5.6, 5.7 and 5.8.

$$d_i(x^l) = \frac{|y(x^{l+1}) - y(x^l)|}{\Delta} \tag{5.6}$$

Where,

$d_i(x^l)$ refers to the influence on the output from the *i*th change on parameter *x*;

$y(x^l)$ refers to the output before parameter *x* changes;

$y(x^{l+1})$ refers to the output after parameter *x* changes;

Δ refers to the magnitude for the parameter change.

Two indexes (μ, σ) are used to indicate the sensitivity of input parameters. μ is used to detect input factors with an important overall influence on the output, calculated by equation 5.7. σ is used to detect factors involved in interaction with other factors or whose effect is nonlinear, calculated by equation 5.8.

$$\mu = \sum_{i=1}^{r} \frac{d_i}{r} \tag{5.7}$$

$$\sigma = \sqrt{\sum_{i=1}^{r} \frac{(d_i - \mu)^2}{r}} \tag{5.8}$$

Where,

d_i refers to the influence on the output when a certain parameter changes for the ith time;

r refers to the total number of changes of a certain parameter.

Since the inputs do not always follow a uniform distribution, the parameters' values in this study are sampled in the space of the quantile of the distributions, each quantile varies in [0,1]. When giving a quantile value for a given input factor, the actual value taken by the factor is derived from its statistical distribution.

Input parameters of UDM include population growth rate, climate change rate and candidate water system update strategies. As the population growth rate and climate change factors have cumulative influences on the efficiency of water system, and qualitative changes are caused by quantitative changes, it is difficult for conventional methods to analyse the influences of these parameters on model output and the differences between the influences of various parameters. Population and climate change factors were used instead.

As little information can be found to achieve possible probability distribution of input parameters, the following Monte-Carlo method is applied to estimate the distribution for each input parameter.

1) Select a time step T_i;

2) Select strategy adopted for each time step in [T_1, T_i];

3) Select population growth rate and climate change rate for each time step in [T_1, T_i]];

4) Run UDM to generate a scenario with households and climate change factor.

5) Repeat step1)-4) for 30,000 times.

5.3 Results and Discussion

5.3.1 Urban water infrastructure implementation pathway

The urban water infrastructure implementation pathway for Scotchman's Creek catchment (2015-2035) generated by the proposed method is shown in figure 5.3.1. The exploration model was run by the cloud computing center of Monash university, with 1 virtual computer as the main control machine for task distribution and result storage, and 32 virtual computers as the operation machine. A total of 2.93 million scenarios were simulated, which took about 1 year and 6 months in real time. The urban development simulation module and water system performance evaluation module accounted for 50% respectively. Both the robustness evaluation module and the adaptive planning module take minutes.

According to figure 5.3.1 (top), when the robustness requirement of the water system is high (acceptable failure rate less than or equal to 1%), the flood resistance ability of the water system can only be met through continuous upsizing of drainage network system. This indicates that among all candidate strategies, the flood resistance capacity from expansion of urban pipe network is the largest, which is consistent with the sensitivity analysis results.

In 2030, a water system with highly upgraded drainage network as well as small amount of WSUD facilities could also meet the needs of the flood prevention, but with the further development of the city, the subsequent derivative system are unable to continue to ensure the reliability of the system, and therefore not have robustness of planning (the inability to transition between scheme). This also indicates that WSUD, represented by distributed rainwater facilities, cannot guarantee that the city is completely free from the threat of flooding either during the recent construction or after the long-term construction. Therefore, in addition to the construction of infrastructure, attention should also be paid to the promotion of non-structure measures (such as relevant policies and publicity, etc.), so as to improve the flood resistance awareness and risk avoidance ability of urban residents as much as possible, and enhance urban resilience from another aspect.

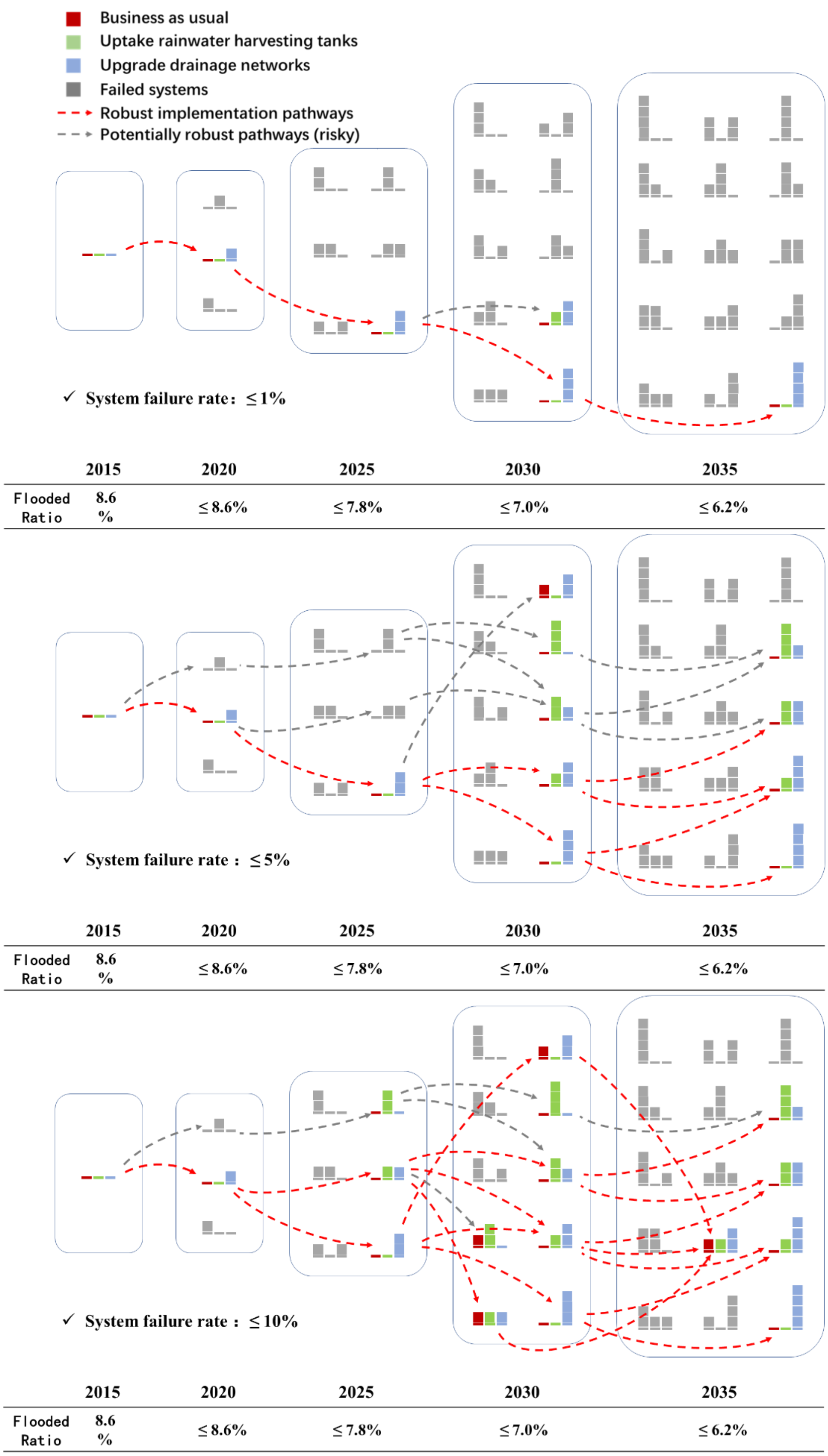


Figure 5.3.1 Urban water infrastructure implementation pathways for Scotchman's Creek

If the expectation of water system robustness is slightly reduced (acceptable failure rate less than or equal to 5%), this proposed method can provide 4 water system construction paths of global robustness optimization and 4 construction paths of local robustness optimization. The combination of sponge facilities and pipe network system was incorporated into the planning path with the improvement of maximum failure rate. As can be seen from figure 5.3.1 (middle), 1) within the urban water systems with high robustness, majorities are still plans dominated with pipe system and assisted with WSUD facilities still. 2) For robust plans dominated by WSUD facilities, the coverage rate of WSUD facilities is at least 10%; 3) In the plan which WSUD completely replaces the pipe system (coverage rate reaches 20%) is not robust enough. This indicates that when the total coverage area of sponge facilities in the city reaches a certain volume (greater than or equal to 10%), the flood disaster in the basin can be effectively reduced, but it still cannot completely replace the status of the pipe network system.

If the expectations of water system robustness is further reduced (acceptable failure rate less than or equal to 10%), the method will provide more path to the water system construction, but it is worth noting that neither the plans with low WSUD coverage and no updated pipe system in the short-term (2020,2025), nor those with only WSUD facilities in the long-term (2035) has high robustness. This shows that if the existing pipe network system is not yet perfect, blindly building WSUD facilities will bear certain risks. However, in the long run, it is still possible for the city to finally achieve the goal of robust water system (locally optimized construction path), but not only use the water system with scattered facilities.

In addition, in the short term, maintaining the existing water system is a basically unworkable strategy that cannot guarantee the effective operation of the water system. While the "business as usual" strategy, although in some stage of the medium and long term, can maintain the robustness of the system, will reduce the robustness of the planning (adaptivity).

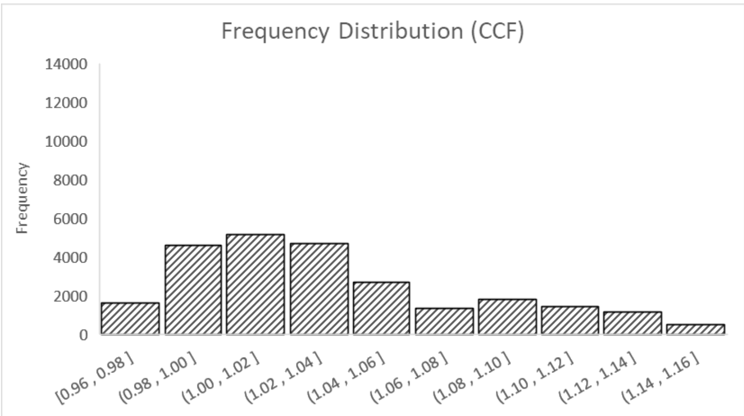
5.3.2 Feasibility of multi-objective pathway

Thanks to the three independent model structure of exploration-evaluation-planning proposed in this chapter, construction pathway planning can be carried out for multiple targets respectively after completion of exploration, and the results can be superimposed and the common construction path can be selected as the multi-objective construction path of water system.

When the construction pathway does not meet the requirements of multiple objectives, there is no need to re-explore like conventional methods. Only the failure assessment matrix (D) and acceptable failure rate (A) in the evaluation module need to be adjusted according to the actual situation until a feasible pathway can be obtained.

5.3.3 Model Sensitivity

The frequency distribution of each input parameter estimated by the Monte-Carlo method is shown in figure 5.3.2. The sensitivity analysis results of the exploration model evaluated by Morris method are shown in figure 5.3.3. The higher the absolute value of the μ, the greater the influence of this parameter on the output result. The higher the absolute value of the σ, the greater the interaction of this parameter with other parameters.



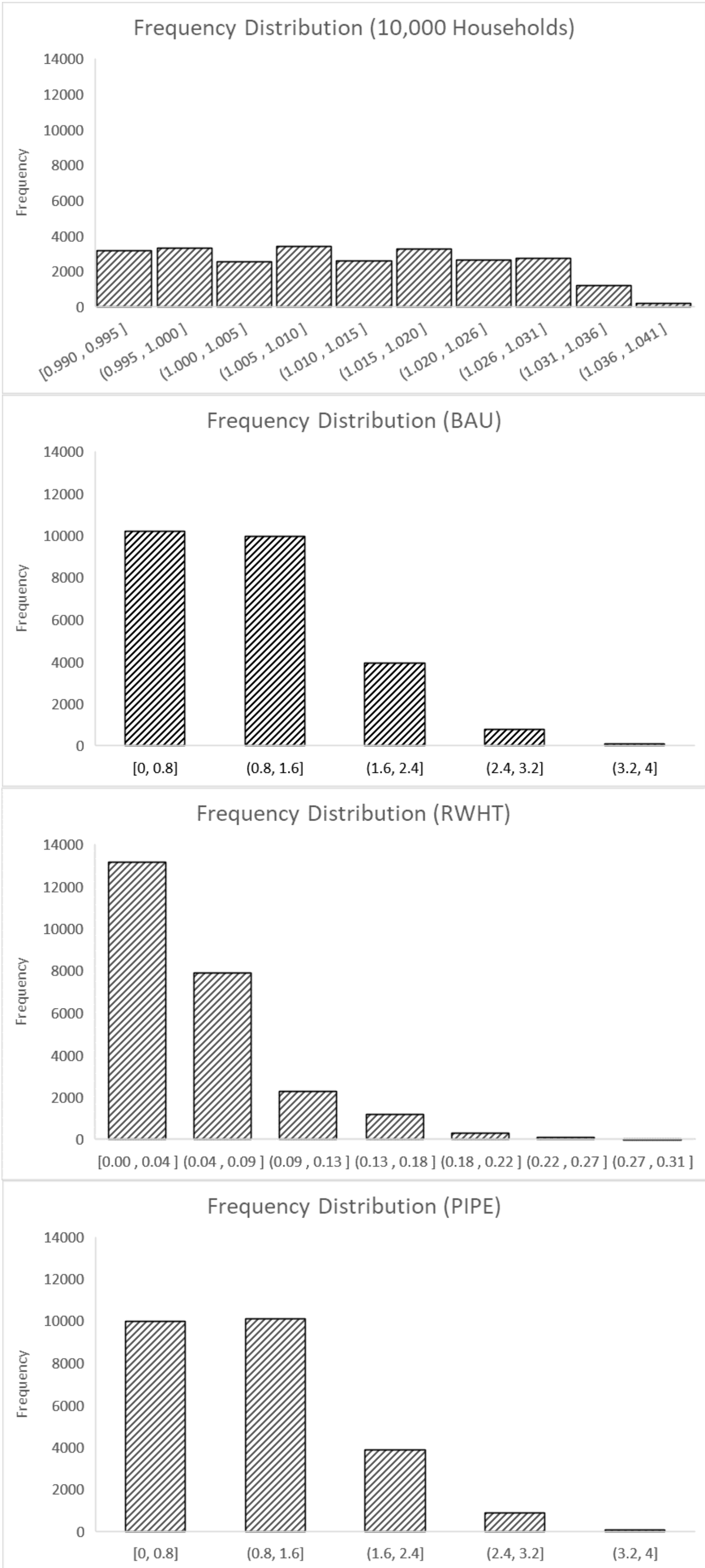


Figure 5.3.2 The frequency distribution of input variables by Monte-Carlo sampling

The results show that the five-year climate change rate (CCF) has the highest positive correlation with the performance of urban water system (number of flooded nodes) and the largest synergistic effect with other parameters, which is consistent with the situation in the real world where climate change leads to the increasing failure of urban water system. It is worth noting that due to the highest sensitivity of climate change factors, the accuracy of its prediction has the greatest impact on the results, and it is very difficult to predict it. Therefore, the results of traditional non-exploratory prediction methods are highly uncertain.

Figure 5.3.3 The sensitivity result of the exploration and evaluation module by Morris method

WSUD strategy and drainage network strategy are negatively correlated with the water system performance, indicating that these two strategies are indeed helpful to reduce flooding. The capacity of traditional network strategy to reduce flooding is obviously higher than that of WSUD strategy, but its influence by other parameters is also significantly higher than that of WSUD strategy. In other words, WSUD facility has a limited capacity to reduce urban flooding, but its stability of reducing capacity is higher.

The capacity of flood reduction is determined by the system capacity of different strategies, but the difference of stability of the capacity reduction may be determined by the spatial characteristic of different strategies. The spatial location of rainwater system is relatively fixed, and the reduction of flooding is not only related to rainfall, but also related to the spatial distribution of WSUD facilities (runoff changes caused by them). Due to its fixed space, it is greatly affected by the other two. As a decentralized system, WSUD facilities have large spatial location variability, and their flood reduction is related to rainfall and land properties, and their runoff reduction capacity is small, so they are less affected by fixed pipe network system.

The strategy of business as usual is positively correlated with the water system performance, but the influence degree is small, and it is also less affected by other parameters. It indicates that this parameter may be a redundant parameter, but its influencing factors are not clear currently (as will be explained in chapter 8), so the parameter is retained in this chapter

Population growth is almost irrelevant to the failure rate of urban water system, and has little interaction with other parameters, which is a redundant parameter for water system. This is because in the UDM module, the existing single-family residential land is changed into multiple houses or apartments to meet the demand of population growth, so the change of land property is minimal and the impact on water system performance is negligible. However, the construction of WSUD facilities in the module will take the opportunity of housing renewal, thus it is not treated as redundant parameters in this chapter.

5.4 Conclusion

In this chapter, three independent modules, global exploration, robustness assessment and adaptive optimization design, are proposed to optimize the construction pathway of water system and design the transition scheme, so as to improve the adaptability and robustness of long-term urban water system planning. The main results are as follows:

1) A three-stage scenario exploration model (exploration-evaluation-adaptability optimization) is developed, which realizes the exploration of urban water infrastructure implementation pathway with multiple strategies and multiple objectives. The proposed parallel exploration module improves the local correlation and comparability between scenarios and avoids the

disadvantages of local optimization in traditional methods. The proposed evaluation module and adaptability optimization module, which are separated from the exploration module, greatly accelerate the assessment speed of the pathway, and realize the design of multi-objective construction path, avoid the risk of failure of path generation caused by the subjective cognition of planners, and improve the practicality of construction pathway.

2) The results enrich the understanding of WSUD facilities and urban water system construction. Experiment showed that WSUD system, in long-term or short, cannot guarantee robust flood prevention, thus more attention should be paid to the application of non-structure measures; When the total coverage area of WSUD facilities in the city reaches a certain volume (greater than or equal to 10%), the flood disaster in the basin can be effectively reduced, but it still cannot completely replace the capacity of the pipe system. In the case that the existing pipe network system is not yet perfect, blindly building only WSUD facilities will bear certain risks. However, in the long run, it is still possible for the city to finally achieve the goal of robust water system (locally optimized construction path), but it is definitely not the water system that only adds WSUD facilities on the existing basis.

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Chapter 6.

Acceleration of pathway exploration by deep learning

6.1 Introduction

In chapter 5, a global exploration model of urban water infrastructure implementation pathway is proposed. By changing the traditional exploration structure, it realizes multi-strategy scenario exploration, avoids the disadvantages of local optimal in traditional methods, and improves the feasibility of the transition design between schemes. It is obvious that the performance and time consumption of exploration are two mutually restricting factors in the practical application. The more scenarios are explored, the higher the reliability of planning and the longer the time consumption.

Unfortunately, there is no way to reduce exploration time without changing the scope of exploration. Therefore, this chapter studies the feasibility of integrating the artificial neural network (multilayer Perceptron, Multi - Layer Perceptron, MLP) with the pathway exploration model, using machine learning to study the scenarios (including urban situation and water system situation), use "global exploration sampling + clustering" instead of global exploration, in order to reduce the feasibility of the computing time.

In recent years, Artificial Neural Networks (ANNs), as a data-drive, self-adaptive and non-linear forecasting tool was applied in various fields such as natural resource management (Mustafa, Rezaur, Saiedi, & Isa, 2012; Ruben, Zhang, Bao, & Ma, 2017; Singh et al., 2017), pattern recognition (Kumar, Singh, & Shahani, 2015; Ripley & BrianD, 2009) , medical diagnosis (Sun et al., 2017) and decision making (Erdem & Hasselmo, 2012; Ivey, Bullock, & Grossberg, 2011). As a matter of fact, the methods and its derivative tool are often used in short-term decision makings or predictions (event scale) rather than long-term planning (strategy scale). To cope with the exploration model, the machine learning algorithm was designed and trained to predict urban water infrastructure performance for individual events while the decision on planning was made based on microscopic strategy performance distribution.

An acceleration module based on machine learning algorithm was developed to predict the performance of urban water system under different city scenarios and reduce exploration time. The following works have been conducted: (1) a comprehensive statistical trial-and-error analysis method is proposed and tested to avoid local optimization of network structure. (2) a neural network was integrated in the explorative adaptation planning to significantly reduce the simulation time, performance was tested and analyzed; (3) a correction method was proposed and tested to minimize the overestimation problem of the designed exploration framework.

6.2 Methods and Data Description

6.2.1 Site Description

The location and project studied in this chapter are the same as that in chapter 5, which is the 20-year long-term plan of Scotchman's Creek catchment water system (2015-2035), as shown in section 5.2.4. Taking the results of the exploration model in chapter 5 as the control group, the differences between the water system construction path generated by the global exploration method and that generated by the global acceleration exploration method (am-ann) were analyzed. The control group data contained 2.93 million scenarios and their water system performance evaluation results, of which 1.73 million were scenarios with uniformly distributed inputs and 1.2 million were scenarios with randomly distributed inputs.

6.2.2 Acceleration module

The proposed accelerated exploration started with a normal exploration and paused when a user-defined amount of simulations had been finished. These simulations (inputs and results) were used as the training set to train an ANN while the exploration continued. The exploration then stopped when a second user-defined amount of simulations had been finished. These extra simulations would be used for validation of the trained ANN. The ANN is trained with different structures and settings and tested on the validation simulations. The errors of the validation are used to choose the best structure and setting, and the ANN does the rest of the exploration by predicting with the scheduled PGR, CCF and add-on strategies (as the normal exploration) but skipping the UDM and SWMM process.

The results in the reference exploration (the scenarios as well as the evaluated system performance) were classified into three sets: the training set (size: 0.1%, 1% or 10%), the validation set (size: 10%) and the test set (size: the remaining data).

The training set was used to train the network (e.g., weights) while the validation set was for adjusting the structure of the network (e.g., number of nodes) [4]. The test set was used to assess the performance of a trained and validated network. In most literature (Abderrahim, Chellali, & Hamou, 2016; Fan, Wang, & Li, 2016; Feng et al., 2015; Lopez, Rene, Boger, Veiga, & Kennes, 2017; Mirici, 2018; Raheli, Aalami, El-Shafie, Ghorbani, & Deo, 2017; Saeidi, Mohammadzadeh, Salmanmahiny, & Mirkarimi, 2017; Sun et al., 2017), as the network structure are usually pre-defined or tested by trial-and-error, the validation sets are usually disused or replaced by the test sets. Under such substitution, the performance of the network is only meaningful for certain sets (the 'test sets'), which have been optimized during the training, rather than for the untrained data which we expect more precise predictions.

6.2.3 Artificial neural network design

Type of ANN

There are several groups of networks such as Feedforward Networks (e.g., Multi-layer Perceptron (Rumelhart, Hinton, & Williams, 1986), the Probabilistic Neural Network (Enke & Thawornwong, 2005), the Dynamic Neural Network (Guresen, Kayakutlu, & Daim, 2011)), Recurrent Networks (e.g., Elman Network (Lee & Chen, 1995), Autoregressive Networks (Kodogiannis & Lolis, 2002)), Polynomial Networks (e.g., Ridge Polynomial Networks (Ghazali, Hussain, Al-Jumeily, & Merabti, 2007), Function Link Network (Hussain, Knowles, Lisboa, & El-Deredy, 2008)), Modular Networks, Support Vector Machine and so forth. (Ramos & Martínez, 2013).

Among these extensive types of ANNs and their derivations, The multi-layer perceptron (MLP), a feedforward multilayer network with non-linear node functions, is the most commonly encountered one (T. D. Pham, Yoshino, & Bui, 2016; Ramos & Martínez, 2013). Practically, MLP shows successful generalization capability, effectiveness and efficiency in forecasting time series (Feng et al., 2015; Raheli et al., 2017; Ruben et al., 2017; Singh et al., 2017), as well as great compatibility coping with different optimization methods or existing models (Raheli et al., 2017; Zadkarami, Shahbazian, & Salahshoor, 2016). Although MLP is usually the better choice or at least the same performance with respect to other proposal networks (Ramos & Martínez, 2013), there remain certain delimitations that have a remarkable impact on the training accuracy and efficiency. Such aspects include the structure of the network, the activation function of nodes, the existence of bias units, the quality and quantity of training and validation datasets, the choice of training algorithm and parameters and so forth. In this paper, the MLP network will be adopted while the design process of these aspects will be investigated and adapted to the case study. The network will be established using PyBrain (Schaul et al., 2010), a modular Machine Learning Library for Python.

The Structure of MLP Network

The MLP usually consists of nodes(units) arranged in three types of layer: the input layer, the hidden layer(s) and the output layer. As Figure 2 shows, each node (unit) has its own output value y and is connected by real-valued weights w to all (and only) the nodes of the subsequent layer. For the ith node in the lth layer nil, let Sil be the set of nodes that connect to nil, f(x) be the activation function of nil, the output value is calculated using Formula (1):

$$y_{n_i^l} = f\Big(\sum_{n_j^m \in S_i^l} w_{ji}^{ml} y_{n_j^m}\Big) \tag{1}$$

where $y_{n_i^l}$ is the output value the ith node in the lth layer; w_{ji}^{ml} is the weight of the connection between this node and the jth node in the mth layer; $y_{n_j^m}$ is the output value of the jth node in the mth layer; f(x) be the activation function of this node.

The input layer receives the input data while the output of output layer refers to the predicted results. Thus, both only requires only 1 layer to fulfil the task. The number of nodes in these layers are determined according to the number of input variables and target variables (Ba, 1997). In some cases, the input and output variables are linearly normalized to (0,1) or (−1,1), to avoid computational problems or to meet algorithm requirement (Lopez et al., 2017; Piotrowski, Napiorkowski, Napiorkowski, & Osuch, 2015; Zhang, Eddy Patuwo,

& Y. Hu, 1998). In this study, such methods were not applied because: (1) with the exploration continues, the input variables will always exceed the range of the existing records while the output variable also has the chance. (2) the weights may undo the scaling.

The number of hidden layers and its nodes has a significant impact on MLP training(Ba, 1997; Laudani, Lozito, Riganti Fulginei, & Salvini, 2015). Simple networks maybe less accurate in learning the problem while complex networks may take excessively long training time. One hidden layer is usually sufficient in most cases (Abderrahim et al., 2016; Bayram, Ocal, Laptali Oral, & Atis, 2015; Fan et al., 2016; Feng et al., 2015; Lopez et al., 2017; Mirici, 2018; B. T. Pham, Tien Bui, Prakash, & Dholakia, 2017; Raheli et al., 2017; Ramos & Martínez, 2013; Saeidi et al., 2017; Sun et al., 2017; Talebi, Nasrabadi, & Mohammad-Rezazadeh, 2018) while sometimes multiple hidden layers shows better learning on certain problems (Zadkarami et al., 2016).

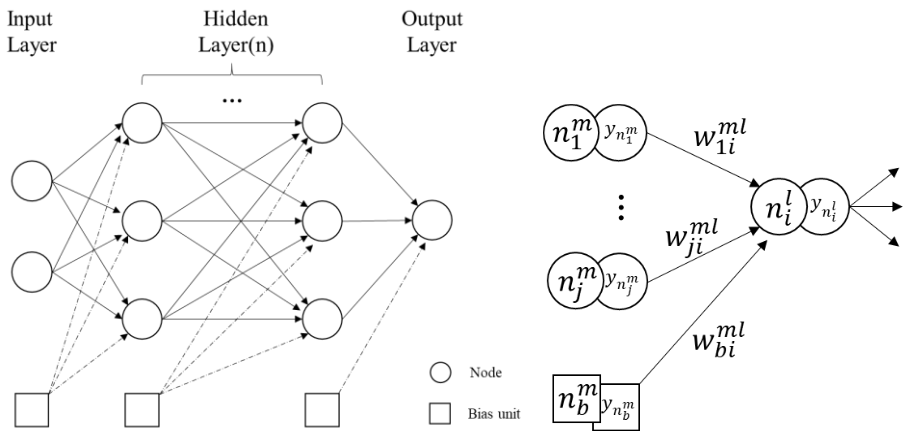

Figure 2. Structure and value propagation of MLP.

The number of nodes in hidden layer is usually determined through a trial-and-error method (Feng et al., 2015; Raheli et al., 2017; Talebi et al., 2018). The range of attempts is usually within 1 to 20 (Abderrahim et al., 2016; Fan et al., 2016; Feng et al., 2015; Lopez et al., 2017; Mirici, 2018; Raheli et al., 2017; Saeidi et al., 2017; Sun et al., 2017), or 3 times the number of input variables (Talebi et al., 2018). The best number of nodes was the one having the smallest mean-square error (MSE) and root-mean-square error (RMSE) and the highest correlation coefficient (r) for the validation data set. (Ruben et al., 2017)

In this paper, the designed MLP consists 1 input layer, 1 hidden layer and 1 output layer. There will be 5 nodes in the input layer representing climate change factor, population, the number of decision take for BAU, RWHT and PIPE within the 20 years and 1 node in the output layer referring to the flooded junctions. No variables will be normalized. The number of nodes in the hidden layer will be determined within 1 to 20 through trail-and-error method.

The Activation Functions

The role of activation function (AF) in MLP is to non-linearize the linear combination of weights and node values passing through from the previous layer. Practically, there are three types of AFs: (1) the analytic AFs, which are classic functions such as Gaussian, Sigmoid and Tanh; (2) the fuzzy AFs, which has faster convergence in training; and (3) the adaptive AFs, which improves the nonlinear response of the network (Laudani et al., 2015). Although the fuzzy AFs perform better on specific problems (Tang, Deng, & Huang, 2016), there is little evidence on the advantage of such AFs in practice. On the other hand, the adaptive AFs also suffer from a more complex and error-prone training algorithm (Laudani et al., 2015). Thus, only classic analytic AFs are considered in this study.

For nodes in the hidden layer, most commonly used AFs are the logistic sigmoid function (Bayram et al., 2015; T. D. Pham et al., 2016; Piotrowski et al., 2015), the tanh function (Humphrey et al., 2017; Talebi et al., 2018; Zadkarami et al., 2016). These two functions are similar in shape while different in output ranges (sigmoid: [0,1], tanh: [–1,1]). For the output layer, most researchers adopt linear function (Bayram et al., 2015; Humphrey et al., 2017; Ruben et al., 2017; Zadkarami et al., 2016).

In this paper, the log-sigmoid function has been used for the hidden layer nodes while linear function has been applied in the output layer to test their performance on handling random noise.

Bias Unit

The bias unit is an extra set of nodes added to all layers but the output layer, which helps to get a better and quicker learning of the network. The output value of a bias unit is fixed value while the weights of connection from the bias unit to the subsequent nodes are still adjustable. The addition of bias unit introduces a threshold value that may influence the activation of the subsequent nodes (Ba, 1997; Lopez et al., 2017), or, from another perspective, helps to move the AF in the subsequent nodes along the x-axis for better learning results. Thus, in most cases, bias units always contribute positively to the network.

Learning Algorithm and Parameter Setting

The traditional and most commonly used training method for MLP is the two-step error-backpropagation method (Lopez et al., 2017; Raheli et al., 2017; Sun et al., 2017). Firstly, the input vector is fed into the input layer, propagating forward through hidden layer(s) to the output layer. Then, the error is calculated in the gradient descent and propagated backward from the output layer through the hidden layer(s) to the input layer, which modifies the weights for every connection between nodes. The training repeats until the network's overall error are less than a predefined learning rate, or until the number of maximum epochs is reached. Learning rate is a damping factor applied to weights correction during training (Laudani et al., 2015), indicating the amount that the weights are updated. Epoch is a measure of the number of times all of the training vectors are used once to update the weights. Obviously, when dealing with huge datasets, it is super time consuming if all the weights are recomputed for each training vector. Thus, there is also a batch-learning term for the backpropagating method, which feeds multiple training samples in one forward/backward pass. The number of samples in one pass is called batch size while such one forward/backward process is count as one iteration.

As the original backpropagation method is likely to be slow (Bayram et al., 2015), improved strategies such as Second-order On-Line training methods have been developed. Although these second-order training algorithms are likely to converge significantly faster than first-ordered backpropagation (Ba, 1997), they require more complex data preprocessing as well as more storage and computational costs. Luckily, there are also several improved first-order backpropagation methods. The most commonly used is the Backpropagation with Momentum (Lopez et al., 2017; Saeidi et al., 2017), which significantly speed up the training process. The momentum is an inertial factor applied to the weights during the back propagate process, which aims to maintain the direction of weight changing (Laudani et al., 2015). The addition of momentum accelerates convergence where the learning quality is good while precisely reduces the number of oscillations where bad (Ba, 1997).

The settings of training parameters are more likely to be empirical and case-dependent. In most cases, the start/fixed learning rate will be in the range of [0.01,0.3] (Abderrahim et al., 2016; Mirici, 2018; T. D. Pham et al., 2016; Saeidi et al., 2017) while the end learning rate within [0.00013,0.001] (Mirici, 2018; Raheli et al., 2017). The number of epochs usually depends on the training data size and the computational capacity, ranging from 200 to 15,000 (Lopez et al., 2017; Mirici, 2018; B. T. Pham et al., 2017; T. D. Pham et al., 2016; Raheli et al., 2017; Saeidi et al., 2017; Zadkarami et al., 2016). Momentum is typically set to 0.9 [22], although the optimal value might be task-specific (Lopez et al., 2017; Mirici, 2018; T. D. Pham et al., 2016).

The designed network structure and learning parameters are shown in Table 1. All combinations of structure and learning parameters were tested with the first 0.1% of data and validated with the following 0.05% data. After the best structure was determined, the network was again tested with different size of training set size to find the best application pattern. The validation set size is half of the training set. The best performing structure and application patter were applied to the case study to study the feasibility of ANN in supporting long-term planning.

Table 1. Designed Neural Network Parameters.

Type	Structure			Activation Function	Bias Units	Learning Settings	
	Name	Layer	Node				
MLP	input	1	5	-	True	training size [1]	0.1%, 1%, 10%
						batch size	1
	hidden	1	1–20	sigmoid	True	learning rate	0.01, 0.1, 0.3
						learning rate decay	1.0
	output	1	1	linear	False	momentum	0.1–0.9
						epoch	500, 1000, 5000

[1] Training size is the percentage of total data used as the training set, tested after the ANN structure being determined.

6.2.4 Validation and evaluation

The performance of learning results was assessed by the root-mean-square error (RMSE), which is a commonly used index in machine learning (Fan et al., 2016; Mirici, 2018; T. D. Pham et al., 2016; Sun et al., 2017). The lower RMSE it is, the better prediction the module makes (Raheli et al., 2017).

RMSE is defined as the absolute value of the estimated error between the predicted result and the observed result, calculated by:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(O_i - P_i)^2}{n}} \tag{2}$$

where O_i is the observed result; P_i is the predicted result.

As the unit of RMSE is case-dependent, the correlation coefficient (r) (Fan et al., 2016; Mirici, 2018; T. D. Pham et al., 2016; Sun et al., 2017) was adopted to compare the training performance with other studies.

$$r = \frac{\sum_{i=1}^{n}(P_i - \bar{P})(O_i - \bar{O})}{\sqrt{\sum_{i=1}^{n}(P_i - \bar{P})^2 \sum_{i=1}^{n}(O_i - \bar{O})^2}} \tag{3}$$

where O_i is the observed result; P_i is the predicted result; $\bar{O}$ is the mean value of the observed result; $\bar{P}$ is the mean value of the predicted result.

Practically, as the decision in long-term infrastructure implementation planning is not scenario-based but strategy-based, the distribution of predict results for each strategy combination should be more convincible than RMSE. Thus, the prediction distribution of outputs was also adopted in this study as the other performance indicator

6.3 Results and Discussion

6.3.1 ANN structure and setting

As mentioned in the previous section, all combinations of structure (number of hidden nodes) and learning parameters (learning rate, momentum and number of epochs) were tested with the first 0.1% of all data (training size = 0.1) and validated with the following 10% of data. For each parameter, the distributions of RMSE for each candidate value under all possible combinations are shown in Figure 3.

By adopting ANN(MLP) in urban water infrastructure performance prediction, the RMSE of such method ranges from 10.97–19.33 nodes with the observed flooded junctions ranging from 20 to 146. For the number of hidden nodes, setting 1 node caused the highest average RMSE (16.62) which may due to the strongest linearity of the network. With the number of hidden nodes rises to 4 nodes, the average RMSE drops gradually to 15.46 where the non-linearity starts to develop effect. From 4 nodes to 20 nodes, the average RMSE keeps stable within (15.13,15.56). Although there is no significant difference in the average RMSE with the number of hidden nodes changing, the distributions of RMSE still have dramatic and irregular variations. These distributions are characterized by the minimum, maximum, Q1, Q3 and mid-values, which indicates 100%, 75%, 50%, 25%, 0% chance of getting a higher RMSE than the given value, respectively. Thus, the lower these values are, the better performance of the network we will get.

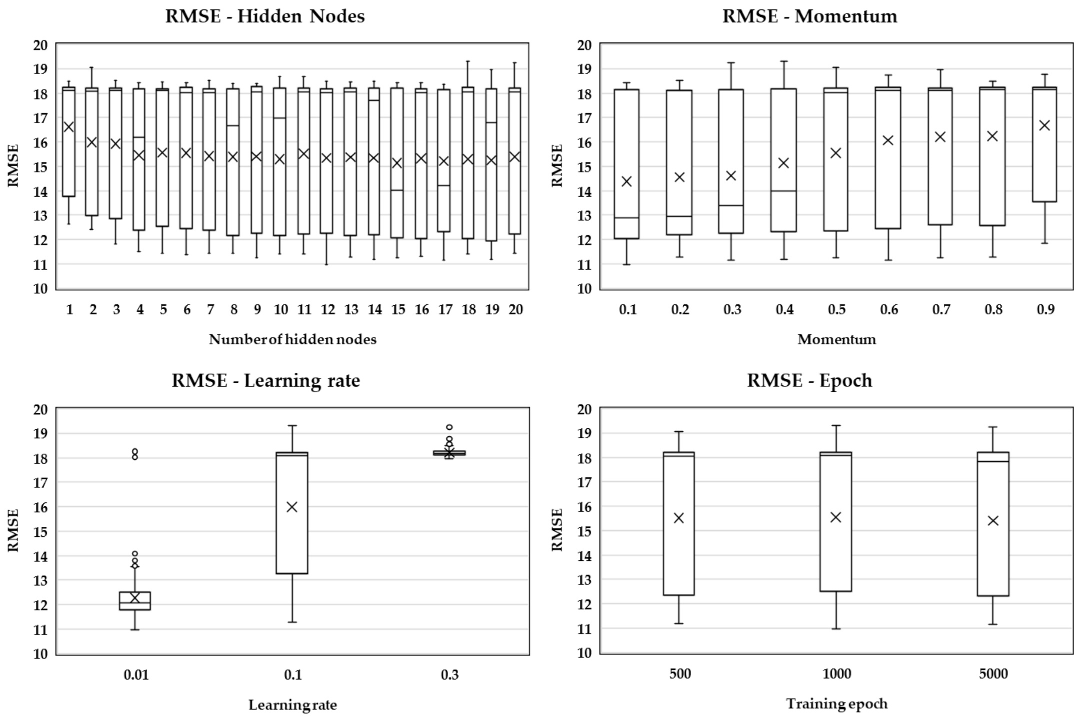

Figure 3. RMSE Distributions under different manipulated variables.

As shown in Table 2, the MLP network with 15 nodes was always in the top 5 well-performed structure and has significant advantages in low mid-value compared to others. The 17 nodes network is slightly better than the 15 nodes one on minimum, Q3 and maximum as well as slightly poor on Q1 and mid-value. Thus, the network of 15 and 17 hidden nodes are selected as the candidate structure for the following studies.

Table 2. Comparison of performance distribution for different number of hidden nodes.

	1st	RMSE	2nd	RMSE	3rd	RMSE	4th	RMSE	5th	RMSE
Min	12	10.97	**14/17**	11.17	19	11.18	9	11.25	**15**	11.26
Q1	19	11.95	18	12.04	16	12.05	**15**	12.08	13	12.16
Mid	**15**	14.02	**17**	14.20	8	16.67	19	16.79	10	16.98
Q3	**17**	18.15	5	18.17	10/12	18.19	13/14	18.20	**15**	18.21
Max	**17**	18.37	8	18.39	9	18.41	6	18.42	**15/16**	18.43

Following the same process, the rest parameters are then determined: momentum = 0.1, learning rate = 0.01, epoch = 5000.

The candidate network was again tested with different size of training set size to find the best application pattern (see Table 3). The result indicates that network with 15 nodes performs better than the 17 nodes one under the select learning parameter, which is within 3 times the number of input variables [38]. Training with the first 10% data will have a significant improvement in reducing the RMSE while maintaining an acceptable time-saving capacity (reduce 80% of the time).

Table 3. ANN performance under different training set sizes.

	Training Size	Hidden Nodes	Learning Rate	Momentum	Epoch	RMSE
Validation set	0.001	15	0.01	0.1	5000	11.5051
	0.01					11.8653
	0.1					9.7961
	0.001	17				12.2593
	0.01					12.5760
	0.1					11.9862
Test set	0.1	15	0.01	0.1	5000	10.5722

The best performing structure and application pattern (Table 3) were then applied to the case study. The overall RMSE for the whole observed data and the predicted data is 10.5722 and the detailed performance of MLP prediction is shown in Figure 4. The overall RMSE is slightly higher than the validation result (9.7961).

The correlation coefficient (r) of the test set was 0.821, which was preferable compared to rs in the other close applications of ANN (flood discharge: 0.683–

0.851 (Seckin, 2011), open-channel junction velocity field: 0.035–0.884 (Sharifipour, Bonakdari, & Zaji, 2018), drought effects on surface water quality:0.819–0.922 (Safavi & Malek Ahmadi, 2015), BOD in river: 0.505–0.821 (Raheli et al., 2017)).

Taking account of the tremendous amount of data in this case study, the above result suggested the proposed statistical trial-and-error method for determining network parameters is feasible and reliable on selecting the best structures.

6.3.2 Accelerated pathway exploration

To analyze the performance variations of different implementation strategy combinations for the urban water system in the case study, boxplots are again used while the upper end of the whiskers is set to 95th percentile (Figure 4). In other word, the probability of a certain system performing better than this upper end is 95%. Thus, the accuracy on the 95th percentile and Q3 is practically more important than that of mid-value, Q1 and minimum.

For strategies containing only rainwater tanks ([0,5.0,0], [0,10.0,0], [0,15.0,0] and [0,20.0,0]), the first two combinations are all included in the training set and share the same distribution with the observed results. For the latter two strategies, the 95th percentile errors are −0.24% and −1.26% respectively while the Q3 errors being −2.28% and −5.68%. This suggests the designed MLP network is effective and has relatively good performance in predicting strategies with spatial randomness. The performance of purely decentralized systems may have stronger and more linear relation with the rainfall events and urban permeability (related to buildings/population), which makes the prediction of these purely decentralized strategies better than the mixed strategies.

For the same reason, the purely business as usual strategies also have good predictions: for [3,0.0,0], Q3 = −0.22% and 95th = 0.18%; for [4,0.0,0], Q3 = −0.77% and 95th= −0.88%. As no additional systems were implemented in these scenarios, the designed network performs well in generalizing the relation between water system performance and rainfall events and urban permeability.

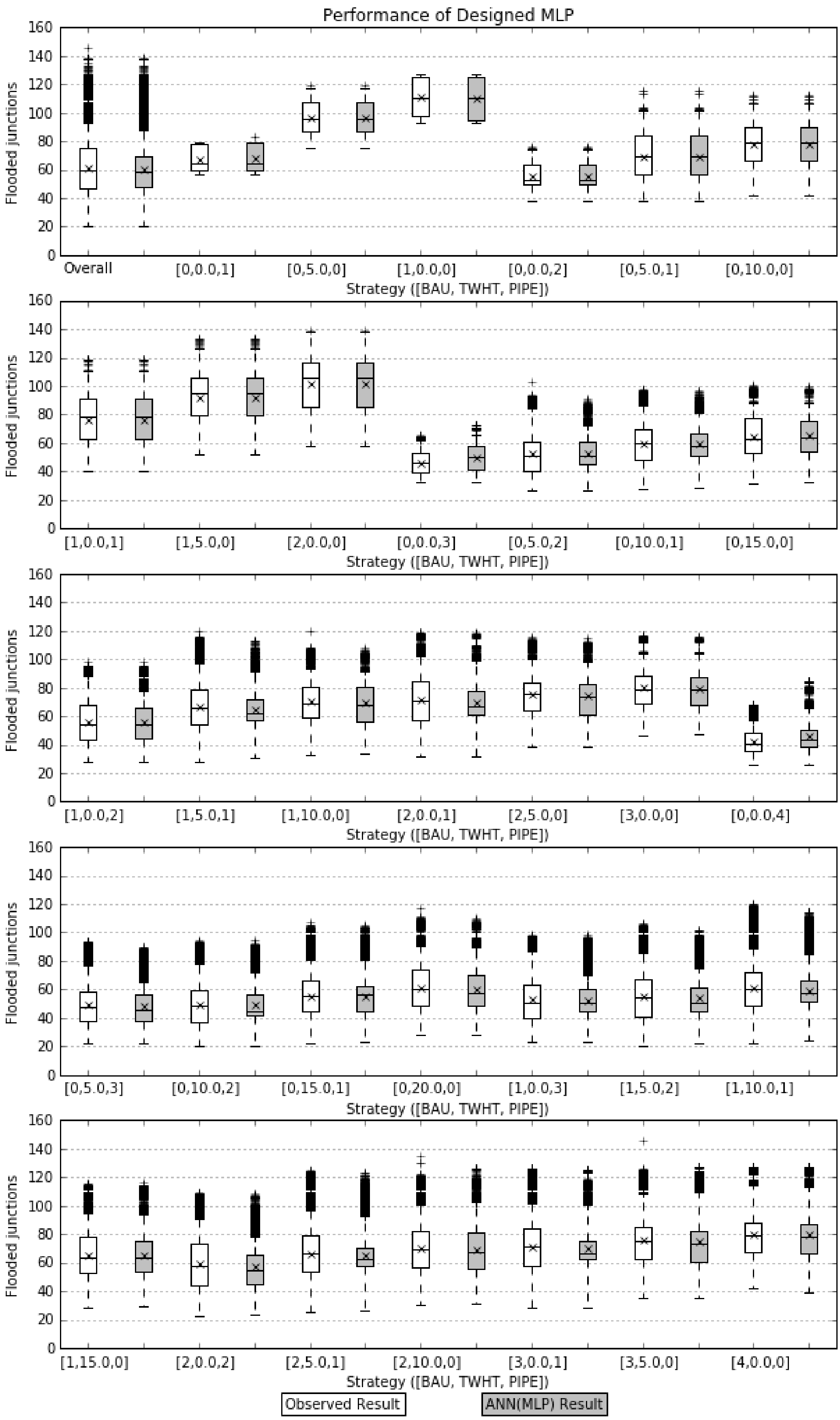

Figure 4. ANN performance for different strategy combinations (supported by Matplotlib (Hunter, 2007)).

For the overall performance, the MLP result has similar minimum, Q1 and mid-value compared to the observed result (min: 20, 20; Q1: 48.1, 47.0; mid: 58.3, 60.0). Whereas the predicted values have a narrower range (20.0–88.44) than the observed ones (20–93) despite the outliers. Such phenomena indicate that the prediction in the high-value events (poorly performed water system in practice) tend to aggregate to the Q3. This suggests that, from an overview perspective, the adoption of ANN supported planning may raise the chance of overestimating the performance of urban water systems.

6.3.3 Correction of the prediction

To make this proposed method applicable and reliable in practice, the error distributions of the result are investigated to solve the overestimating problem. As shown in Figure 5, all errors of Q3 lie between (−10.56%,8.76%) and 95th percentile between (−18.91%,14.95%). The majority of these errors are negative, indicating universal overestimations of the urban water system.

As Table 4 shows, the adoption of safety coefficient could effectively raise the error from negative to positive (from overestimation to under estimation) while slightly enlarge the standard deviation of the errors.

As these errors are related to the network structure and its final status, a safety coefficient, which comes from the validation process, is adopted to adjust the final output of the network. By investigating the observed data and the predicted data in the validation set, a multiplicator or exponent can be calculated out and applied for the test set. As the 95th percentile is the dominant factor of this case study, the safety coefficient also comes from the 95th percentile of the validation (multiplicator:1.0910, exponent:1.0272).

Table 4. Mean ± SD error of adopting the safety coefficient.

	Observed Error	Multiplicator	Exponent
Q3	−2.29% ± 4.28%	3.38% ± 4.73%	3.43% ± 4.72%
95th percentile	−3.13% ± 6.34%	2.63% ± 7.15%	2.96% ± 7.32%

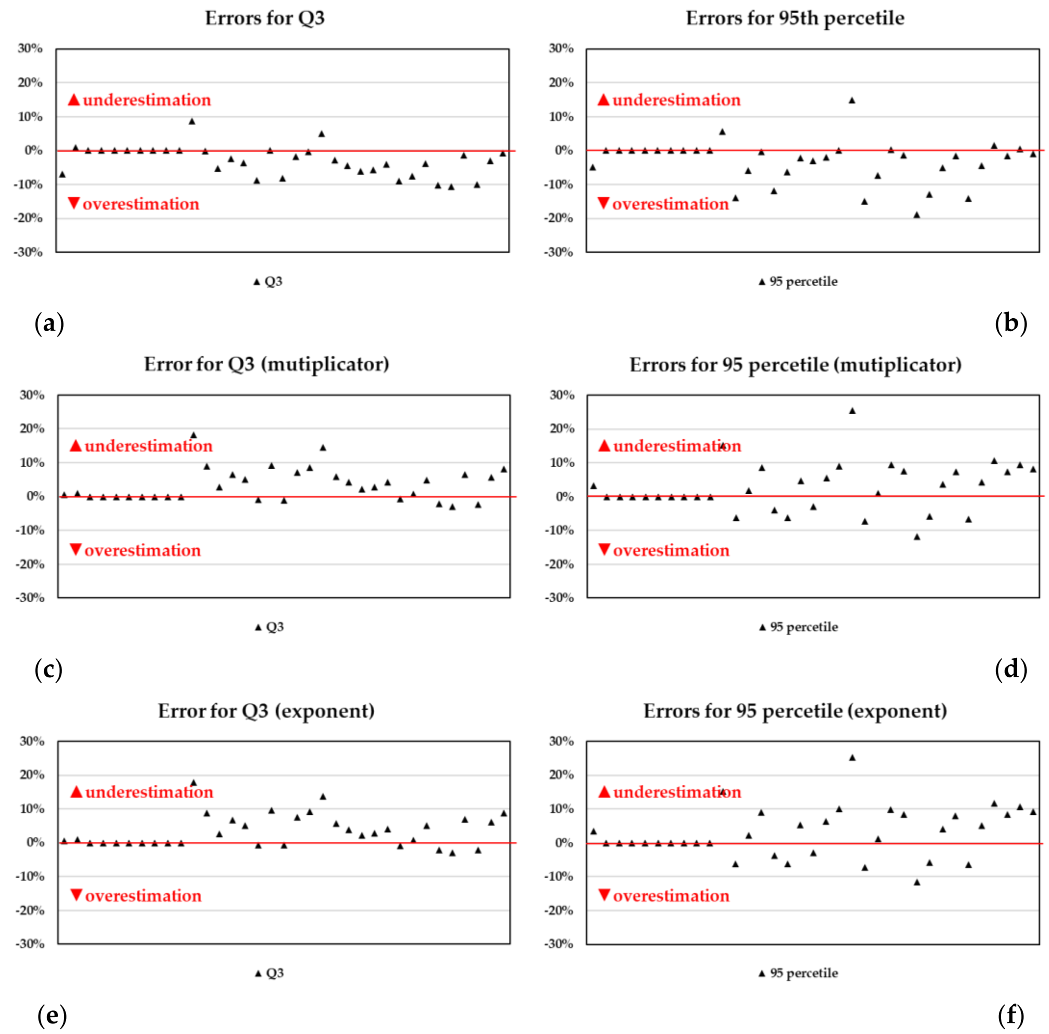

Figure 5. Error distribution of MLP predicted result and corrected result ((a,b) observed errors for 95th percentile and Q3; (c,d) corrected errors for 95th percentile and Q3 by multiplication; (e,f) corrected errors for 95th percentile and Q3 by exponent).

The result of correction is shown in Figure 5. There is no obvious difference between correction with multiplicator and exponent. The corrected errors of Q3 lied in −3.05% to 18.24% (multiplicator) and −2.96% to 17.87% (exponent) while that of the 95th percentile in −11.69% to 25.41% (multiplicator) and −11.60% to 25.36% (exponent).

6.3.4 Urban water infrastructure implementation pathway (accelerated by deep learning)

As shown in Table 5, the accelerated exploration identified all robust drainage infrastructure status in the reference exploration while overestimated three. The corrected accelerated exploration identified most robust drainage infrastructure status in the reference exploration while underestimated one. The underestimated one has no influence on the plan generation as there is no connectable route in the previous decision year. Thus, the correction is essential and effective to raise the robustness of the proposed accelerated exploration.

Table 5. Robust progressive goal for Scotchman's Creek.

	Reference Exploration	Accelerated Exploration	Corrected Accelerated Exploration
2020	[0,0,1][1]	[0,0,1]	[0,0,1]
2025	[0,0,2]	[0,0,2]	[0,0,2]
2030	[0,0,3]	[0,0,3]	[0,0,3]
	[0,5,2]	[0,5,2]	[0,5,2]
	[0,10,1]	[0,10,1]	[0,10,1]
	[0,15,0]	[0,15,0]	-
	[1,0,2]	[1,0,2]	[1,0,2]
	-	[1,5,1]	-
2035	[0,0,4]	[0,0,4]	[0,0,4]
	[0,5,3]	[0,5,3]	[0,5,3]
	[0,10,2]	[0,10,2]	[0,10,2]
	-	[1,5,2]	-
	-	[2,0,2]	-

[1] [BAU,RHWT(%),PIPE].

Notably, for 95th percentile, the majority of errors are controlled within ±10%. The two outliers represent the two pure strategies of upgrading pipes, [0,0.0,3] and [0,0.0,4]. Although there are great errors on these two strategies (underestimation of water system), the origin system performance of them is good enough that the errors have no influence on identifying them as good strategies (not influencing decision). This error also indicates that different from purely decentralized strategies, such purely centralized strategies which have only relations with rainfall events, do not have a preferable prediction at all.

Such a result indicates that when using the MLP to predict a black box problem, such as the urban water system in the case study, there should be at least two related input factors for each variable (the candidate infrastructure, e.g., pipe, rwht) to ensure reliable prediction.

6.4 Conclusion

Aiming at the time-consuming of the global exploration model proposed in chapter 5, deep learning (artificial neural network method) is introduced into the exploration model to speed up the exploration process while ensuring the prediction accuracy. The main conclusions are as follows:

1) Multi-layer perceptron (MLP) network is integrated with the exploratory model proposed in chapter 5, and being applied to the water system construction pathway planning of Scotchman's Creek watershed in Australia. While providing the same pathway, the accelerated global exploration model (AM - ANN) proposed in this chapter can reduce the simulation time by 80%.

2) the MLP network adopted in this chapter has different predictive performance for different types of water system scenarios. The prediction of water systems that update only decentralized facilities is better than that update both centralized and decentralized facilities, while the latter is better than that update only centralized facilities. The above results, combined with the results of sensitivity analysis in chapter 5 (the degree of interaction between parameters and other parameters), illustrate that MLP neural network should screen related input variables according to the sensitivity of input variables to improve the accuracy of output variables.

3) An optimization method of neural network structure was proposed by using statistical analysis instead of variable-control method. Under the condition of using 10% of the training data, 10% of the verification data and 80% of the test data, the validation error (RMSE) is 9.7961, the test error (RMSE) is 10.5722, and the correlation coefficient (r) is 0.821. The results show that this method can help to design more reasonable neural network (avoid local optimization of design parameters) and obtain more stable neural network with less training data. Although this optimization method takes a little more time than the traditional control variable method, it provides enough stability and precision to make up for this deficiency.

4) The correction method proposed in this chapter based on the verification process can effectively solve the problem that the overall prediction of urban water system performance by the global accelerated exploration method (AM-

ANN) tends to be optimistic (3.13%±6.34% more flooded nodes than the control group). The multiplication factor and power factor calculated according to the verification data can control the prediction tendency problem in an acceptable range and have very limited influence on the final decision (2.63%±7.15% more flooded nodes than the control group). This correction method does not reduce the error but shifts the error to the conservative estimate to make the decision made by the forecast result more reliable, so this correction method has more practical significance.

6.5 Reference

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Chapter 7.

Acceleration of pathway exploration by dynamic learning

7.1 Introduction

Compared with the global exploration module in chapter 5, the accelerated global exploration module (AM-ANN) proposed in chapter 6 can greatly reduce the computation time without affecting the final decision, but still has the following disadvantages:

1) The training set is based on the first 10% of time series data of the control group, so the scenario distribution of each time step in the training set is uneven and irregular. For neural network, the quality of training set is one of the important factors that affect the quality of prediction. Therefore, when applying the accelerated global exploration module (AM-ANN), it will be affected by the uncertainty of the time step distribution of scenarios in the training set.

2) After the completion of the neural network training, the result is used in all subsequent scenario prediction and have no adaptation capacity toward changes. E.g. When the subsequent exploration range exceeds the original training range, the proposed method can only predict based on the old learning result. Thus the AM - ANN will be affected by the uncertainty of the training set quality.

Therefore, the accelerated module (AM) should not only provide reliable performance on prediction, but also be robust to deal with uncertainties such as data quality, quantity and time order.

Rough set theory (Pawlak, 1982) , as a mathematical tool for analyzing and conceptualizing inaccurate, uncertain or vague knowledge, has been successfully applied in bioinformatics, medicine and data mining (Chen, Li, Luo, Horng, & Wang, 2015; Liang, Wang, Dang, & Qian, 2014; Ye, Chen, & Ma, 2013) to cluster and predict scenarios.

A dynamic accelerated global exploration module (AM - RST) is developed based on rough set theory in this chapter which, in the process of exploring, could continue to improve prediction accuracy by self-updating. The parameter "significance" is introduced, which changes the expression of causal rules in traditional rough theory. By expressing causal rules in a probability way, the influence of error distribution on decision-making is compensated, and the accuracy of (AM-RST) in practical application (especially when dealing with big data) is improved.

7.2 Methods and Data Description

7.2.1 Site Description

The location and project studied in this chapter are the same as that in chapters 5 and 6, which is the 20-year long-term plan of Scotchman's Creek catchment water system (2015-2035), as shown in section 5.2.4. Taking the results of the exploration model in chapter 5 as the control group, the differences between the water system construction path generated by the global exploration method and that generated by the global dynamic acceleration exploration method (AM-RST) were analyzed. The control group data contained 2.93 million scenarios and their water system performance evaluation results, of which 1.73 million were uniform scenarios and 1.2 million were random scenarios.

7.2.2 Dynamic acceleration module by rough set theory

The working flow of AM-RST is shown in figure 7.2.1. The core idea is to improve the accuracy of prediction by learning from events that cannot be accurately predicted.

Different from traditional machine learning modules, this module can distinguish predictable and unpredictable scenarios through the causal rule deducted from rough set theory. The rules are in the form of "if... (scenario)..., then... (prediction of performance) ...”, which does not always (and does not need to) contain all parameters. Thus, the entire rule set does not cover all sampling space, nor have an intersection. At the same time, each causal rule has its corresponding credibility, which depends on the users’ decision to apply.

The reduction in computing time from AM-RST is embodied in two aspects: one is to skip the SWMM assessment process of the predictable scenarios, the second is to skip the UDM process of the predictable scenarios in the last time step (these scenarios do not need to go through SWMM as they will be predicted by AM-RST, neither go through UDM for subsequent city scene exploration as they are in the last step). In the global exploration model proposed in chapter 5, the time consumption of UDM development simulation module and SWMM evaluation module is 50% respectively, so the dynamic accelerated global module proposed in this chapter should have the same computing time reduction capacity as the accelerated global module in chapter 6.

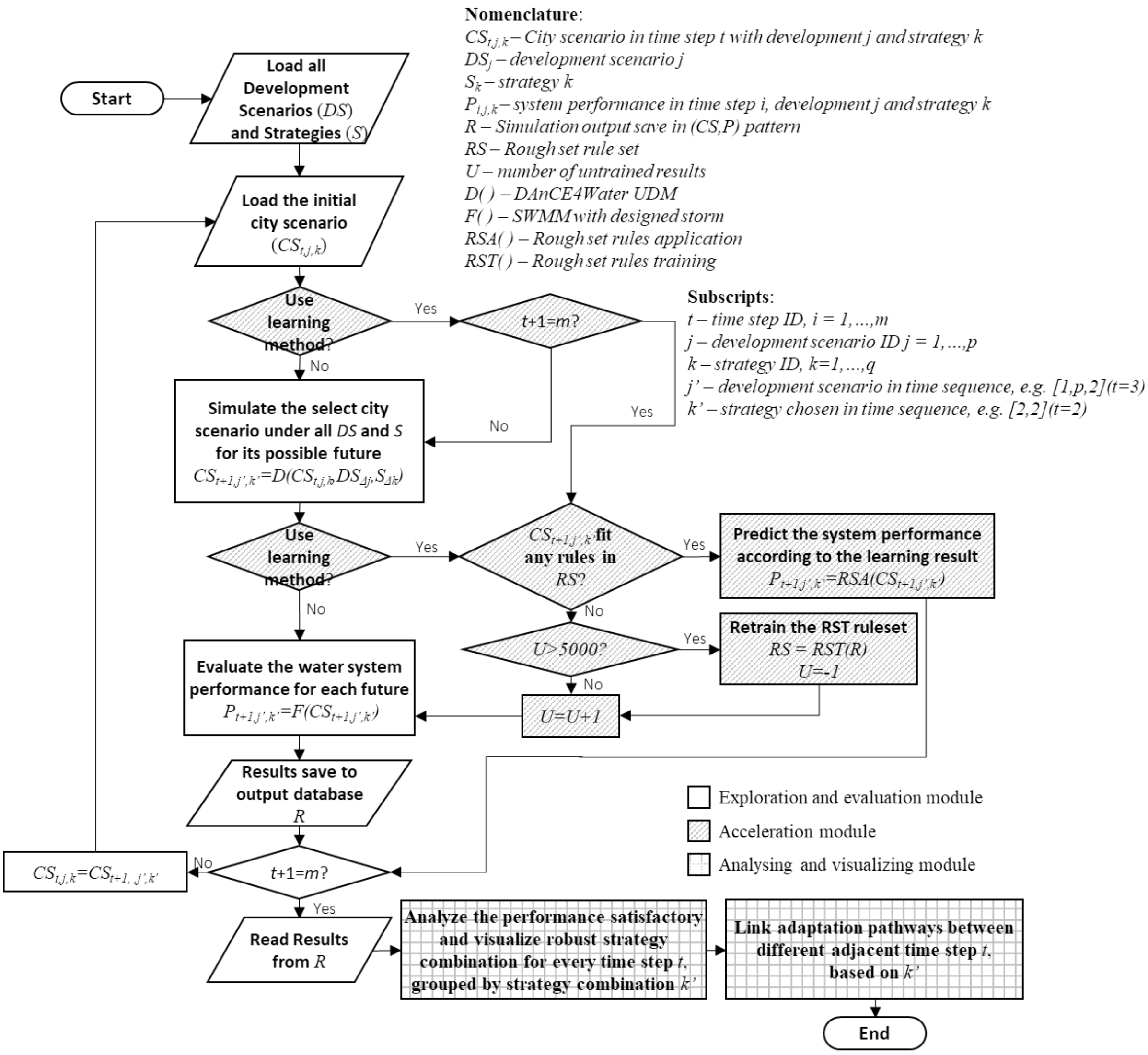


Figure 7.2.1 The dynamic learning module based on rough set theory

As shown in figure 7.2.1, dynamic learning module of AM-RST requires a user-defined minimum number of data (U) to trigger the (re-)training. When global explore module operation, accelerate module will first estimate the city scenario (urban status, water system status) and compare it with the existing causal rules, then process the data into UDM for the predictable scenarios (if it's the last time step, skip), and make the prediction. The result will store into the database R'; If the scenario cannot be predicted by the causal rule, the normal exploration steps (go through UDM, SWMM evaluation) are applied, and the scenario parameters and water system performance evaluation results are stored in the training database R. When the total amount of data in the training database reaches U, the rough causal rule (re-)training algorithm is triggered (Walczak & Massart, 1999) to update the causal rule set.

Compared with existing researches (Doherty, Lukaszewicz, Skowron, & Szalas, 2006), there are two significant differences in the application of rough set theory in this chapter: 1) The data volume is huge (about 2.93 million scenario simulations), which far exceeds other existing studies 2) The corresponding relationships between "scenario" (future of the city and the drainage system plan) and "water system performance" are fuzzy, especially for the "scenarios" with random spatial layout (e.g. decentralized systems). These two characteristics lead to the fact that the same "scenario" (with different layout of decentralized system with same total area) can correspond to many different "water system performances”, so the accuracy of causal rules concluded by the traditional rough set algorithm is very low and cannot be applied. In order to solve this problem, this study did not attempt to accurately cluster " scenario " and "water system performance" through optimization methods, but recorded the probability distribution of "water system performance" under similar "scenario" to represent the uncertain fluctuation of "water system performance" under a "scenario".

Thus, the index "Significance (Sig)" is proposed as the highest probability of "water system performance" in a causal rule (in other word, under a certain scenario), which represents the uniformity of " performance" distribution in the rule (the lower the value is, the more uniformly distributed it is). When the Significance of a rule reaches the minimum user-defined value (Sig_{min}), the rule will be saved into the causal rule set and be applied in the prediction of the dynamic accelerated exploration module (AM-RST). In the process of prediction, the predicted "performance" will be randomly selected according to the recorded probability of the applying rule.

7.2.3 Validation and evaluation

Root mean square error (RMSE, see equation 6.2) and correlation coefficient (r, see equation 6.3) are used to evaluate the performance of AM-RST. the lower RMSE, the higher r, the better prediction effect of the model (Raheli, Aalami, El-Shafie, Ghorbani, & Deo, 2017).

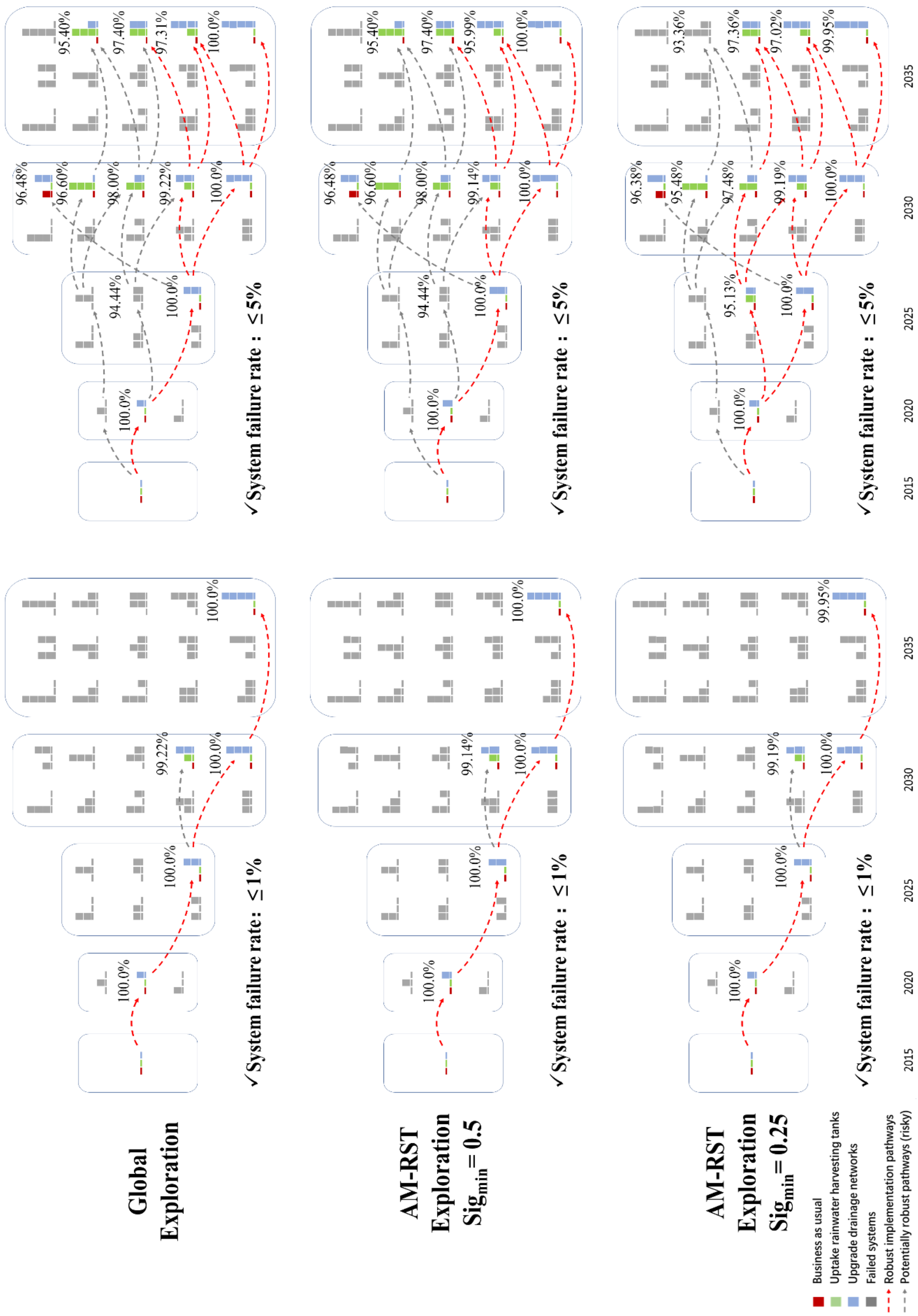
Since there are both prediction results and exploration results in the process of dynamic accelerated global exploration (AM-RST), two root-mean-square errors, RMSE and RMSE*, are used to evaluate its prediction ability. RMSE is the root mean square error of all prediction results, which reflects the accuracy of prediction of this module. RMSE* is the root mean square error of all exploration results (including prediction), which reflects the degree of influence of the application of this module on the final decision (water system construction pathway).Meanwhile, since the concept of "significance" is introduced, different minimum significance will affect the reduction ability of operation time. Therefore, the time reduction in SWMM evaluation module, UDM exploration module and global exploration module are also used as evaluation basis.

7.3 Results and Discussion

7.3.1 Urban water infrastructure implementation pathway (accelerated by dynamic learning)

Figure 7.3.1 shows the construction pathway of Scotchman's Creek catchment generated by the global exploration method and the dynamic accelerated global exploration method. The Sig_{min} in AM-RST is 0.5 and 0.25.

When Sig_{min}=0.5, the selection of rough causal rule is the most rigorous. The rule will be recorded only when the probability of a water system performance value is higher than 50%. In this circumstance, the path generated by the dynamic accelerated global exploration module is exactly the same as the global exploration under the condition that the acceptable failure rate of the system is 1% and 5% (including the determination of the robustness and adaptive planning of the water system scenario).



Global Exploration
AM-RST Exploration Sig_{min} = 0.5
AM-RST Exploration Sig_{min} = 0.25
√System failure rate : ≤1%
√System failure rate : ≤5%
2015
2020
2025
2030
2035
Business as usual
Uptake rainwater harvesting tanks
Upgrade drainage networks
Failed systems
Robust implementation pathways
Potentially robust pathways (risky)

Figure 7.3.1 The construction pathway of Scotchman's Creek catchment generated by the global exploration method and the dynamic accelerated global exploration method.

When Sig_{min}=0.25, the selection of rough causal rule is more tolerant. The rule will be recorded when the probability of a certain water system performance value is higher than 25%. When the acceptable failure rate of the system is 1%, the path generated by the module is exactly the same as that of the global exploration. This is because when the acceptable failure rate of the system is very low, there are too few scenarios of the water system with robustness, so the prediction accuracy cannot be fully reflected. When the acceptable failure rate of the system is 5%, the module also shows an optimistic estimate for some situations. According to its prediction results of water system scenario [0,5.0, 1] in 2025, the failure rate of the system was calculated to be 4.87%, while the failure rate of the system calculated according to the global exploration method was 5.56%. Therefore, there was a mis-determination. This error caused two "local optimized path " was convicted for "global robust path", which leads a certain degree of unforeseen risk to the planners, even if the risk is not high (Δ = 0.69%)

On the whole, even if the most tolerant Sig_{min} is adopted for AM-RST, the effect of errors on the robustness determination of water system (based on the difference of system failure rate) is no more than 2%, and the conservative estimations are far more than the optimistic ones. Therefore, the dynamic accelerated global exploration module proposed in this chapter can be applied to the exploration of urban water system construction path, and the prediction accuracy has little influence on the final decision.

7.3.2 Evaluation of the self-learning process

As Sigmin affects the selection of rough causal rules, the efficiency of dynamic acceleration exploration module varies with different Sig_{min}. The performance of module prediction accuracy and operation time reduction under different Sigmin is shown in table 7.3.1.

The results show that with the reduction of Sig_{min} (0.5→0.25), the reduced computation time by skipping the SWMM evaluation module increases from 8.34% to 41.17%, and the computation time by skipping the UDM deduction module increases from 8.11% to 40.15%. Since UDM module and SWMM module each account for about 50% of the exploration time, and the computation time cut by skipping the two modules is very similar, according to the structure of the acceleration module, most of the predictions are made at the last planned time node. This is because the mode of the exploration model is exponential, so the number of scenarios at the last planning time syep accounts for about 80% of the total.

Table 7.3.1 The prediction performance of AM-ANN under different Sig_{min}

Sig_{min}		0.500	0.475	0.450	0.425	0.400	0.375	0.350	0.325	0.300	0.275	0.250
r		0.9418	0.9300	0.9136	0.8421	0.7959	0.7702	0.7909	0.6982	0.7202	0.7001	0.6963
RMSE		16.28	16.88	16.22	18.41	18.49	18.17	16.82	19.31	18.06	18.84	19.18
RMSE*		6.63	7.42	8.25	11.83	13.49	14.14	13.15	17.20	15.94	17.03	17.52
Time saving	SWMM	8.34%	9.70%	12.98%	20.72%	26.64%	30.30%	30.53%	39.70%	38.99%	40.97%	41.74%
	UDM	8.11%	9.31%	12.55%	20.07%	25.83%	29.49%	29.62%	38.88%	37.88%	39.97%	40.73%
	Total	16.45%	19.01%	25.53%	40.79%	52.47%	59.79%	60.15%	78.58%	76.87%	80.94%	82.47%

At the same time, with the decrease of Sigmin, the proportion of operation time reduced by skipping SWMM module is gradually increased, indicating that with the increase of the tolerance of causal rules, the accelerated exploration module predicts more scenarios of earlier planned nodes, which is consistent with the original intention of the design.

The reduction of overall operation time increased from 16.45% to 82.47%. During the reduction of Sigmin, the reduction of operation time in the early stage was relatively large, while the change in the later stage was relatively stable. In this process, RMSE increased from 16.28 to 19.18 and RMSE* increased from 6.63 to 17.52. It can be seen that, with the decrease of Sigmin, the prediction error does not increase significantly (RMSE), but the total prediction amount increases significantly (RMSE*). Compared with the error (10.5722) of the accelerated global exploration module (AM-ANN) in chapter 6 of this paper, the error is higher under the same operation time reduction condition.

With the decrease of Sigmin, the correlation coefficient r decreased from 0.9418 to 0.6963, and the prediction result maintained a strong correlation with the reference value of the control group. However, it is acceptable compared with other applications of artificial neural network (0.7760 (Pham, Yoshino, & Bui, 2016), 0.890 (Ruben, Zhang, Bao, & Ma, 2017), 0.735-0.857(Raheli et al., 2017)). However, compared with the accelerated global exploration module (AM-ANN) in chapter 6 of this paper (0.8210), the correlation coefficient r is relatively low under the same operation time reduction condition.

It is important to note that although the dynamic accelerated global exploration module (AM-RST) has a relatively poor performance on RMSE and r, compared to AM-ANN), but the prediction of such method tend to be more conservative estimates (the actual system performance will be better than the prediction). While the problem of optimistic estimation (the actual system performance will be worse than the prediction) in AM-ANN, although could be corrected by algorithm, still remains large uncertainties in final decision. Therefore, the AM-RST proposed in this chapter is more suitable for the exploration of the construction pathways of urban water system.

7.3.3 Analysis of the background noise

According to section 7.3.2, although the RMSE and correlation coefficient r of the dynamic accelerated global exploration module (AM-RST) are not as good as that of the accelerated global exploration module (AM-ANN), the robustness evaluation accuracy based on its prediction results is better. Meanwhile, with the decrease of Sigmin, the RMSE increase is not significant (+2.90) and the initial RMSE is relatively large (16.28). This indicates that the prediction results of the global dynamic accelerated exploration module (AM-RST) have large background noise, which does not change with the changes of module parameters, and is caused by the algorithm's own defects.

The detailed prediction process under Sigmin=0.5 was analyzed in this section (in this case, the prediction error is the smallest, so the background noise can be located more accurately). The results show that the background noise mainly originates from the following two parts:

1) Part of the background noise is caused by the spatial randomness (uncertainty) of the WSUS facility layout. As the strategy of "uptake rainwater harvesting tanks" will randomly construct WSUD facilities on constructible land in the exploration model, its layout has spatial randomness and its influence on water system efficiency is uncertain. Table 7.3.2 shows a set of inputs and predicted outputs that conform to the same rough causal rule. As can be seen from the table, since Sigmin is set to screen rules and probabilistic output is adopted, the prediction results of the first two scenarios are relatively accurate, and the overall error (from the perspective of robustness evaluation of water system) is not large. But in the same water system update scenario, as the WSUD facilities' spatial randomness, there is huge differences in the water system performance (the latter three have 19.3% - 40.9% less flooding than the previous two). As the AM - RST deduct its rule from the first two scenarios, it directly predicts the latter three scenarios, which leads to a great error.

This indicates that the dynamic accelerated global exploration module has the problem of preconception in the induction of causal rules. That is to say, some current scenarios do not show their uncertainties (for example, WSUD facilities have little impact on water system when their total volume is small, so their spatial distribution does not show its impact on water system in the early phase), and the causal rules concluded by AM-RST module will prejudice such scenarios. When the uncertainties of these situations show up in the later stage, the existing AM-RST algorithm cannot recognize this problem, and then predict these scenarios based on the inherent causal rule, leading to large background noise.

Table 7.3.2 The performance fluctuation of urban water system due to WSUD spatial distribution and the related prediction errors

Year	CCF	Population	BAU	RWHT	PIPE	Observation	Prediction
2035	1.1025	11504	0	15	1	88	86
2035	1.1025	11500	0	15	1	84	87
2035	1.1025	11509	0	15	1	71	86
2035	1.1025	11509	0	15	1	55	86
2035	1.1025	11502	0	15	1	52	87

2) Another part of the noise is due to the misunderstanding of "business as usual" strategy (redundant data issues). When investigating into the prediction process, 8,217 scenario predictions (around 3.36% of the total scenarios predicted) were found relevant to the " business as usual" strategy while there were only three rules related to this strategy. All the three rules contain only the "business as usual" strategy in the “if… (scenario)…” part. This means a lot of scenarios with “business as usual" as well as other water system upgrade strategies are applying these three rules, making their performance prediction far from correct and resulting in a certain amount of background noise. The reason for this problem is that the strategy of "business as usual" does not make any changes to the water system. According to the sensitivity analysis results in chapter 5, its influence on the water system efficiency and synergistic effect with other parameters are small, so it is a redundant parameter. However, the AM-RST module cannot identify the redundancy of this parameter, so it tries to generalize its rules, thus causing errors.

It is worth noting that, although the population is also a redundant parameter according to the sensitivity analysis results, it has little impact on the AM-RST module due to its small change range (3%-6%), while BAU has a large change range (0-4), so it has a big impact.

7.3.4 Robustness of the dynamic acceleration module

Since the AM-RST's training data is inputted in the time order of the exploration, and may have the potential problem of preconception, different input processes may affect the effectiveness of the module. Therefore, three random time sequences (randomly scrambling control data) was applied to the module with Sigmin=0.25 to investigate the robustness of the module (including the mean value of various indicators, standard deviation and relative standard deviation). The results are shown in table 7.3.3. When Sigmin=0.25, AM-RST has the highest global error RMSE* and prediction error RMSE, so its robustness is the worst which is as well representative. The results show that the AM-RST module has extremely robust computing time reduction ability (relative standard deviation <1%) and prediction accuracy (relative standard deviation <2%).

Table 7.3.3 Performance of AM-RST under different input sequences

Sig_{min}=0.25		Control Group	Sequence A	Sequence B	Sequence C	Average	STD	RSTD
r		0.6963	0.6877	0.7121	0.6876	0.6959	0.0100	1.43%
RMSE		19.18	18.65	18.41	18.65	18.72	0.28	1.50%
RMSE*		17.52	16.94	16.67	16.94	17.02	0.31	1.82%
Time saving	SWMM	41.74%	41.18%	40.98%	41.17%	41.27%	0.28%	0.69%
	UDM	40.73%	40.15%	39.86%	40.15%	40.22%	0.32%	0.79%
	Total	82.47%	81.33%	80.85%	81.33%	81.50%	0.60%	0.73%

It is worth noting that the time series of training data not only has no obvious effect on the efficiency of AM-RST module, but also has very little effect on the background noise. However, this phenomenon does not overrule the conclusion that preconceptions and uncertain data are the main background noise. This phenomenon is caused by background noise, which is not caused by data errors, but by data incompleteness (that is, the error is not caused by incorrect understanding of the scenarios, but by incomplete understanding of the scenarios).

7.4 Conclusion

A dynamic accelerated global exploration method (AM-RST) is proposed in this chapter which improves the robustness of acceleration process. The parameter "significance (Sig)" is introduced to offset the influence of error distribution on decision-making by expressing the causal rule in a probability manner and improve the accuracy of AM-RST module in practical application. The main conclusions are as follows:

1) With the most tolerant Sig_{min} in dynamic accelerated exploration, the prediction results tend to be a conservative estimate, and with probabilistic output. These prediction ensures minimal error in water system robustness analysis (error in system failure rate is less than 2%), and therefore AM - RST module can be applied to the exploration of urban water system construction pathways.

2) with the decrease of Sig_{min} (0.5→0.25), the reduction of simulation time increased from 16.45% to 82.47%, the prediction error RMSE increased from 16.28 to 19.18, the errors are slightly higher than that of the AM-ANN module. However, the overall prediction of AM-ANN module has the problem of

optimistic estimation, which leads to large uncertainty for the final decision. Therefore, AM-RST module is more suitable for the exploration of the urban water system construction pathways.

3) There is a large background noise in the prediction of AM-RST module, which does not change with the changes of module parameters, mainly due to the spatial randomness of sponge facility layout (the problem of uncertainty) and the misunderstanding of “business as usual” strategy (the problem of redundant data). This indicates that the AM-RST module is susceptible to preconception and may form prejudice in the process of induction of causal rules.

4) In the exploration of different time series, the AM-RST module shows extremely robust computing time reduction ability (relative standard deviation <1%) and prediction accuracy (relative standard deviation <2%). The timing sequence of the exploration process also has a very small impact on the background noise, indicating that the background noise brought by uncertainty always exists but is stable in AM-RST, and the noise level exactly reflects the uncertainty level

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Chapter 8.

Conclusions and future work

8.1 Research implications

8.1.1 Planning under uncertainties

The quantity and quality of data, as well as the planners who deals with it, are two of the typical uncertainties in a planning process. In this thesis, a practical decision support method, the Hierarchical Fuzzy Decision-Making (HFDM), was proposed to simulate the manual planning/evaluation process under inadequate data, and tested against traditional Multi Criteria Decision-Making method (MCDM) in a decentralized system planning.

The GIS fuzzification process can maintain the dominant characteristics of spatial units, take into account the adjacent environmental parameters and make reasonable adjustments to express important hidden information. The integrated fuzzy inference design can simulate the manual evaluating process and reduces the custom parameters by 58% compared with the conventional method.

Results indicates that the proposed method, to some extent, reduces the uncertainty of basic data (by digging all possible information that could influence a decision) and user subjective factors (by simulating decision process to avoid manual misjudgement) in planning decisions.

8.1.2 Robust urban water infrastructure implementation pathways

As mentioned in section 2.6, the latest long-term planning approaches are still considering their strategies independently and their planning usually cannot have more than two goals. In this thesis A three-stage scenario exploration model (exploration-evaluation-adaptation) is developed, which realizes the exploration of urban water infrastructure implementation pathway with multiple strategies and multiple objectives. The proposed parallel exploration module improves the local correlation and comparability between scenarios and avoids the disadvantages of local optimization in traditional methods. The proposed evaluation module and adaptability optimization module, which are separated from the exploration module, greatly accelerate the assessment speed of the pathway, and realize the design of multi-objective construction path, avoid the risk of failure of path generation caused by the subjective cognition of planners, and improve the practicality of construction pathway.

8.1.3 (Dynamically) learning scenario exploration

The three-stage pathway generation model have promising speed on multiple-objective evaluation while its exploration and evaluation process can take extreme long time. To make the model applicable, two acceleration modules were developed copping with the exploration module and the evaluation module. 1) Artificial neural network method is introduced into the exploration model to speed up the exploration process while ensuring the prediction accuracy. With the same pathway provided, the accelerated global exploration model (AM - ANN) can reduce the simulation time by 80%. This module better prediction of water systems that update only decentralized facilities than that update both centralized and decentralized facilities, which is better predicted than that update only centralized facilities.

2) A dynamic accelerated global exploration method (AM-RST) is proposed which improves the robustness of acceleration process. The parameter "significance (Sig)" is introduced to offset the influence of error distribution on decision-making by expressing the causal rule in a probability manner and improve the accuracy of AM-RST module in practical application. With the decrease of Sig_{min} (0.5→0.25), the reduction of simulation time increased from 16.45% to 82.47%, and the prediction errors are slightly higher than that of the AM-ANN module. However, the overall prediction of AM-ANN module has the problem of optimistic estimation, which leads to large uncertainty for the final decision. Therefore, AM-RST module is more suitable for the exploration of the urban water system construction pathways. In the exploration of different time series, the AM-RST module shows extremely robust computing time reduction ability (relative standard deviation <1%) and prediction accuracy (relative standard deviation <2%).

8.2 Practical implications

8.2.1 ‘Planning’ model

As mentioned in section 1.1, the traditional long-term planning approaches are more likely to be evaluation tools which was used in a ‘manual plan – computational evaluate – manual adjust’ pattern. The model proposed in this thesis was a literally ‘planning’ tool which after setting all parameters, computationally explores all possible scenarios, evaluates all possible strategy plans and optimize adaptation pathways. As the results (urban water infrastructure pathways) was generated by global exploration pattern, the robustness of the plan is creditable as long as the evaluation module is reliable (which is the commonly used SWMM in this case).

The result pathways could be directly used by decision makers as they could always find what stage the city is currently at in the graph (as it is a global exploration). Adaptation routes can be adopted as long as they are happy to take the known risk (acceptable failure rate).

8.2.2 Co-system planning model

A co-planning method between centralized (sewer) and decentralized (WSUD) systems in the long-term was also proposed in this thesis. The method was developed on the concept of reflect interactions and feed backs among different system plans in their long-term planning. This approach could more rationally simulate the decisions of planners during a long-term ‘implementation’ process.

8.2.3 Macro understanding of centralized and decentralized systems

The urban water infrastructure implementation pathway of Scotchmen’s Creek enriches the understanding of WSUD facilities and drainage system construction. Results showed that:

1) WSUD system, in long-term or short, cannot guarantee robust flood prevention, thus more attention should be paid to the application of non-structure measures.

2) When the total coverage area of WSUD facilities in the city reaches a certain volume (greater than or equal to 10%), the flood disaster in the basin can be effectively reduced, but it still cannot completely replace the capacity of the pipe system.

3) In the case that the existing pipe network system is not yet perfect, blindly building only WSUD facilities will bear certain risks. However, in the long run, it is still possible for the city to finally achieve the goal of robust water system

(locally optimized construction path), but it is definitely not the water system that only adds WSUD facilities on the existing basis.

8.3 Research limitations

8.3.1 Scope of the case study

The case study used in this thesis have several unsatisfactory:

1) For the Hierarchical Fuzzy Decision-Making (Chapter 3), the WSUD-depended drainage system planning (Chapter 4) and the robust pathway generation model (Chapter 5 - 7), three different sites were chosen as case study areas, which greatly broke the consistency of the proposed method. The reason of choosing different case studies instead of one was majorly due to the compatibility between research scope and case scope, as well as the data availability of different sites. In brief, the case of Scotchman's creek is much smaller and was therefore the preferred size for testing the methodology in explorative modellings (to reduce the overall runtime). Whereas a larger catchment (Elster Catchment) was required for the network generation to provide adequate information (e.g. network structure in topology) in the proper scale and a more rural one (with very a small centralized system, Yangchen Lake Peninsula) was required to ensure more accurate and differentiated result for decentralized system planning.To reduce the impact of this problem, the following hypothesis were made in this thesis:

I. It was shown in chapter 3 by case study that the Hierarchical Fuzzy Decision-Making is effective in interpreting spatial hidden information and could have more rational assessment on vulnerability. Thus, a hypothesis was made in chapter 4 that the same method would work in Elster Creek case study and the vulnerability map used in chapter 4 was assumed to be generated by this method (which is actually derived from existing network layout) so that the two proposed method theoretically could be integrated.

II. It was proved in chapter 4 by case study that the proposed co-system planning method could have feedbacks among the planning of the system. Thus, a hypothesis was made in chapter 5 that the same method could work in Scotchman's Creek case study and the strategy status in each time step would have impact on strategies in the next time step (which is actually realized using stochastic process) so that the two method theoretically could be integrated. This hypothesis had very limited impact on the accuracy of robust pathway generation as that model was using a global exploration method, in which all scenarios would always be evaluated someday. The impact of the hypothesis is only on the possibility of reaching the ‘accurate answer’ in a shorter time.

2) The pathway generation model was only tested in a small catchment in Melbourne, where there might be significant difference (lower building density, higher natural soil infiltration rate, etc.) compare to other region such as China. Some of the results may not be accurate if applied in case studies in other areas or larger catchments.

3) The objectives and strategy options used in this thesis is quite limited, due to computational time. Changing or increasing the amount of strategies and objectives might have an influence on the acceleration performance and prediction accuracy (of machine learning).

8.3.2 Incompletable global exploration

It took extreme long time for the global exploration model to run a ‘reference’ result (for the acceleration model to compare with). Theoretically, it would took forever if the exploration is true ‘global’ but the result won’t differ much as long as the sampling point is enough. In the thesis, the ‘reference’ global exploration result can’t be fully proved to have sufficient sampling points. Thus, some results derived from the robust pathways might not be accurate. Notably, the performance of acceleration module is still rational and referable, as they have been proved to be able to have accurate prediction with the same set of data. In other word, if given the data from an exploration with ‘sufficient’ sampling points, the proposed acceleration module will also have good predictions.

8.3.3 General applicability of the acceleration module

Due to the time constraint, both acceleration modules are tested on a single case study. The applicability of the proposed modules to other cases remains unknown. Especially for the AM-ANN module, it is not clear whether the trained result is more efficient on the particular case (on future scenario) or on the performance of combined drainage systems (on drainage system plans). However, the time reduction by AM-ANN will always be stable due to the algorithm (The ANN can always predict after trained, so the time saving capacity is fixed), while the accuracy of prediction might depend on cases.

8.4 Future works

8.4.1 More comprehensive co-system planning

The WSUD-dependent drainage network planning method proposed in this study considers the extension of old and new pipe networks in the process of urban expansion, but does not cover the reconstruction of old urban areas and adjustment of plot planning; The relevant feedback factors only consider the complementary plans such as decentralized facilities planning, but do not cover the restricted plans such as underground pipe corridor planning and road planning. Economic evaluation elements only consider the total consumables, not the construction amount, these aspects need to be further improved, in order to achieve a real overall planning.

8.4.2 Better learning algorithms

The global acceleration module (AM-ANN) proposed in this study has a good prediction ability for the situation where only the distributed facilities/spatial distribution strategy is updated, and a large prediction error for other situations. Meanwhile, the global dynamic acceleration module (AM-RST) has an opposite performance. It remains to be further explored whether we can take advantage of these two kinds of methods to form an efficient and dynamic comprehensive accelerated exploration method.

For the AM-RST, the contributor to the huge background noise is still unclear. Future studies could look into the land use layout of the case study, unsatisfying convergence point, or limitation of the algorithm.

8.4.3 Dynamic objectives and strategies

As a long-term planning tool, the proposed model in this thesis haven’t considered the situation where technology upgrades (better performance of the existing infrastructure), new strategy options (new infrastructure), new objectives (which can’t be reflect by existing performance indicators). These unknown unknows would be some of the large challenges to long-term planning tools, as all of them required a new/extra explorations which, 1) can’t predict the prediction performance of acceleration module to these factors; 2) can’t predict their performance as a servicing system; 3) might overturn the existing robust pathways, which will require to redo a broader exploration than the existing one.

8.4.4 Global exploration

Global exploration is a method that most researchers try to avoid due to its time and effort consumption. For a long time, researchers hope to replace global exploration by local exploration in the smallest possible scope and avoid falling into local optimization by various optimization methods. However, global exploration is always the one with the lowest uncertainty among all methods. With the rapid development of machine learning in recent years, there are a lot of problems to be further explored in the application field of global exploration.

8.5 Final remarks

In summary, this research has resulted in a model that allows the exploration of urban water infrastructure implementation pathways for multiple objectives with multiple strategies.

The thesis has provided scholarly contributions related to long-term infrastructure planning and co-system planning. With some improvement, it could provide a valuable tool for policymakers and practitioners to evaluate robust plans to adapt to future.