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Systems Analysis For Urban Water Infrastructure Expansion With Global Change Impact Under Uncertainties

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SYSTEMS ANALYSIS FOR URBAN WATER INFRASTRUCTURE EXPANSION WITH GLOBAL CHANGE IMPACT UNDER UNCERTAINTIES

by

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ABSTRACT

Over the past decades, cost-effectiveness principle or cost-benefit analysis has been employed oftentimes as a typical assessment tool for the expansion of drinking water utility. With changing public awareness of the inherent linkages between climate change, population growth and economic development, the addition of global change impact in the assessment regime has altered the landscape of traditional evaluation matrix. Nowadays, urban drinking water infrastructure requires careful long-term expansion planning to reduce the risk from global change impact with respect to greenhouse gas (GHG) emissions, economic boom and recession, as well as water demand variation associated with population growth and migration. Meanwhile, accurate prediction of municipal water demand is critically important to water utility in a fast growing urban region for the purpose of drinking water system planning, design and water utility asset management. A system analysis under global change impact due to the population dynamics, water resources conservation, and environmental management policies should be carried out to search for sustainable solutions temporally and spatially with different scales under uncertainties. This study is aimed to develop an innovative, interdisciplinary, and insightful modeling framework to deal with global change issues as a whole based on a real-world drinking water infrastructure system expansion program in Manatee County, Florida. Four intertwined components within the drinking water infrastructure system planning were investigated and integrated, which consists of water demand analysis, GHG emission potential, system optimization for infrastructure expansion, and nested minimax-regret (NMMR) decision analysis under uncertainties. In the water demand analysis, a new system dynamics model was developed to reflect the intrinsic relationship between water demand and changing socioeconomic

environment. This system dynamics model is based on a coupled modeling structure that takes the interactions among economic and social dimensions into account offering a satisfactory platform. In the evaluation of GHG emission potential, a life cycle assessment (LCA) is conducted to estimate the carbon footprint for all expansion alternatives for water supply. The result of this LCA study provides an extra dimension for decision makers to extract more effective adaptation strategies. Both water demand forecasting and GHG emission potential were deemed as the input information for system optimization when all alternatives are taken into account simultaneously. In the system optimization for infrastructure expansion, a multiobjective optimization model was formulated for providing the multitemporal optimal facility expansion strategies. With the aid of a multi-stage planning methodology over the partitioned time horizon, such a systems analysis has resulted in a full-scale screening and sequencing with respect to multiple competing objectives across a suite of management strategies. In the decision analysis under uncertainty, such a system optimization model was further developed as a unique NMMR programming model due to the uncertainties imposed by the real-world problem. The proposed NMMR algorithm was successfully applied for solving the real-world problem with a limited scale for the purpose of demonstration.

Key Word: nested minimax regret (NMMR), multiobjective interval linear programming, life cycle assessment (LCA), carbon footprint analysis, water demand, system dynamics modeling, system analysis

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LIST OF ACRONYMS/ABBREVIATIONS

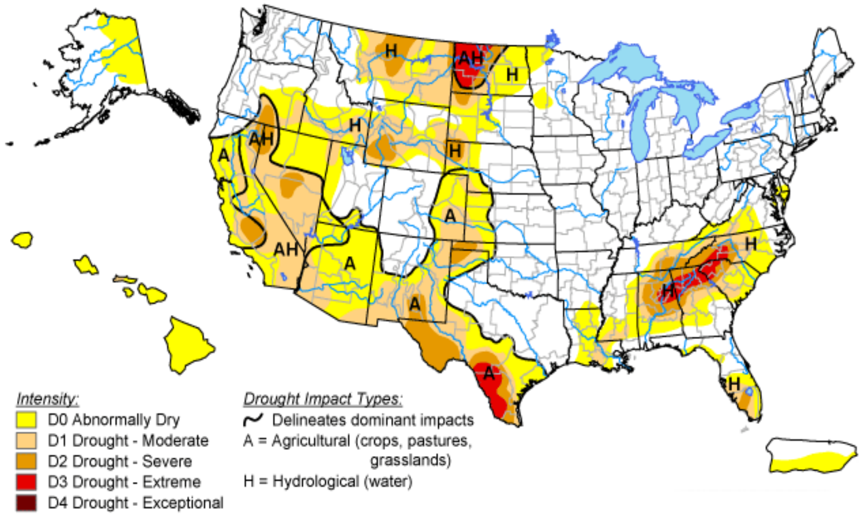
AAI	Average Annual Income
ANN	Artificial Neural Networks
ASR	Aquifer Storage and Recovery
ECWF-1	East County Wellfield I
EPA	Environmental Protection Agency
ESI	Environmental Sustainability Indicator
ESSD	Environmentally Sound and sustainable Development
GHG	Greenhouse Gas
GWP	Global Warming Potential
LCA	Life Cycle Assessment
LCI	Life Cycle Inventory
MARS	Manatee Agricultural Reuse Supply
MARS-I	Manatee Agricultural Reuse Supply, Phase I
MARS-II	Manatee Agricultural Reuse Supply, Phase II
MARS-III	Manatee Agricultural Reuse Supply, Phase III
MARS-IV	Manatee Agricultural Reuse Supply, Phase IV
MCUD	Manatee County Utility Department
MIA	Most Impacted Area
MLP	Multi-layer Perception
MOILP	Multiple Objective Interval Linear Programming
MPWF	Mosaic Phosphate Wellfield

NMMR	Nested Minimax Regret
PR/MRWSA	Peace River Manasota Regional Water Supply Authority
RBF	Radial Basis Function
SCEM-UA	Shuffled Complex Evolution Metropolis Algorithm
SWFWMD	Southwest Florida Water Management District
SWUCA	Southern Water Use Caution Area
TQM	Total Quality Management
UR	Unemployment Rate
WEST	Water Energy Sustainability Tool
WTP	Water Treatment Plant
WUCA	Water Use Caution Area
WUP	Water Use Permits
WWTP	Wastewater Treatment Plant

CHAPTER ONE: INTRODUCTION

1.1 Background

Global change impact including climate change, population growth and economic development are universally recognized. In the past few years, drought impacts affecting big metropolitan water supplies alone have plagued Maryland and the Chesapeake Bay in 2001 through 2002, Lake Mead in Las Vegas in 2000 through 2004, the Peace River and Lake Okeechobee in South Florida in 2006, and Lake Lanier in Atlanta in 2007 that especially affected the water resources distribution in three states - Alabama, Florida, and Georgia. In February 2008, eight major US water agencies united to form the Water Utility Climate Alliance, acknowledging that plans for future investment in water infrastructure must be made to accommodate climate change projections (SFPUC, 2008). On March 28, 2008, Doyle Rice reported in USA TODAY that the historic drought that has gripped much of the southeastern US has eased in recent weeks, according to the most recent US Drought Monitor release. However, the region is not out of the woods yet, with the peak water usage season just ahead. Most recently, on May 13, 2008, the US Drought Monitor (see Figure 1-1) showed that about 18% of the Southeast remains either in severe or extreme drought. Although there currently is no immediate public health threat posed by the Southeastern drought, it does pose significant challenges to policy makers and utility companies to maintain an adequate supply of potable water in the future.



source: National Drought

Figure 1-1 U.S. Drought Monitor for May 13, 2008

The planning of water resources systems is associated with various objectives with complicated supply-demand conflicts (Luo et al., 2003). Urban water supply systems typically require the construction of impoundments (storage reservoirs) to be able to meet demand during periods of low river flow such as drought as well as population growth and migration. The proper management of these water supply systems will need to understand both the environmental (e.g., climate factors) and human (e.g., population and economic factors) dimensions of global change to identify the potential impact on water supply and demand. Water consumption estimates are typically based on population projections and anticipated economic growth. As a consequence of climate change, population growth and economic development, additional sources water supplies from stormwater reuse, to wastewater reclamation, to permit exchange with other sectors, to more surface water impoundments, and to aquifer storage and recovery (ASR) will eventually become essential via an either centralized or decentralized approach, or even both. Effective and adaptive management strategies through the use of the systems engineering approach may be needed to handle the level of sophistication and meet the requirements of global change impact under the framework of total quality management (TQM).

The Manatee County, Florida, is located in the Southern Water Use Caution Area (SWUCA) due to the depletion of the Upper Floridian Aquifer and its entire western portion of the County is designated as part of the Most Impacted Area (MIA) within the Eastern Tampa Bay Water Use Caution Area (WUCA) relative to the SWUCA. WUCA is defined by Southwest Florida Water Management District (SWFWMD) as the area where excess water withdrawals from Floridian aquifer are concerned. Yet, with the population growth and economic development, Manatee County have experienced water demand shortage and the county is forced to find alternative sustainable solutions to meet changing water demand and to minimize the total system costs and environmental impacts at the same time. Due to its complexity, the water supply system in Manatee County turns out to be a good study area for demonstration.

1.2 Study Framework

This study focuses on the water supply systems in Manatee County, Florida, USA. Manatee County water supply facilities work plan (i.e., the work plan hereafter) released in 2008 (Board of Country Commissioner, 2008) describes the study area, the water supply and demand, and its relationships of water supply with neighboring counties. The following description in section 1.2 was adapted from the report for an overview.

1.2.1 Brief Introduction

Manatee County is located in the SWUCA, including Polk, Hardee, Manatee, Hillsborough, Desoto, and Sarasota counties, within the area of Upper Floridian Aquifer which is being depleted rapidly (Board of Country Commissioners, 2008). The western portion of the County is designated as the MIA, a part of the Eastern Tampa Bay Water Use Caution Area

(Eastern Tampa Bay WUCA) relative to the SWUCA (see Figure 1-2). According to the work plan, the County has experienced large residential and tourist population growth and this trend is predicted to continue. For the anticipated future, water supply capacity may become insufficient to fulfill the rapidly increasing water demand. It is essential to study the adaptive management strategies from new facility construction to alternative water source development for the future demand-supply conditions while contributing the minimal impacts to the global climate change.

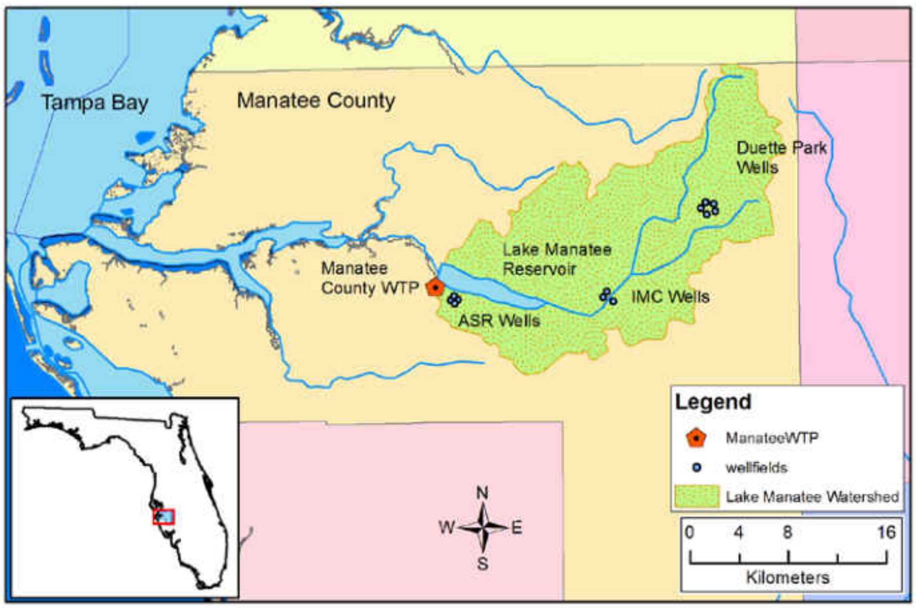


Figure 1-2 The location of study area

1.2.2 Current Water Supply And Existing Facilities

Current water supply sources consist of both surface water and ground water sources. Surface water sources come form Lake Manatee, a man-made reservoir on the Manatee River. It allows a 132,110.9 m^3d^{-1} (34.9 million gallons per day) permitted annual average withdrawal. Current ground water sources come from two wellfields: East County Wellfield I (ECWF-1) and the Mosaic Phosphate Wellfield (MPWF). ECWF-1 permits 60,513.6 m^3d^{-1} (15.986 million gallons per day) average annual withdrawals and MPWF permits 7,419.4 m^3d^{-1} (1.96 million gallons per day) average annual withdrawals. A total capacity of 200,043.9 $m^3 d^{-1}$ (52.8 million gallons per day) is available from current water supply sources. There is one water treatment plant (WTP) next to Lake Manatee and three wastewater treatment plant (WWTP) located over the County. The maximum-day operating capacity of the WTP is 317,974.6 m^3d^{-1} (84 million gallons per day) among which 204,412.2 m^3d^{-1} (54 million gallons per day) is for surface water treatment and 113,562.4 m^3d^{-1} (30 million gallons per day) is for ground water treatment. Located next to the Lake Manatee WTP, there are Aquifer Storage and Recovery (ASR) wells which are used to inject treated potable water into the Florida Aquifer for storage and withdraw the water back when the surface water source is lost during drought seasons. ASR wells have been in operation at the Lake Manatee WTP since 1986 for buffering during periods of low demand and high surface water flow. The ASR wells are permitted to maintain up to 11,356,235.3 m^3 (3 billion gallons) in storage with a combined capacity of 37,854.1 m^3d^{-1} (10 million gallons per day). Figure 1-2 shows the location of Lake Manatee WTP, the ASR Wells, Lake Manatee surface water and the two wellfields. Recently, Manatee County has completed the Manatee Agricultural Reuse Supply (MARS) system to distribute reclaimed water to agriculture users and other users who currently pump water from the Florida Aquifer for irrigation purposes. The saved ground water use credits thus become the net benefits that can be used for future potable water sources.

1.2.3 Water Demand

Principal customers of Manatee County water supply are retail customers, significant users, and wholesale customers. Significant users refer to those customers with water demand >94.635 m^3d^{-1}, while retail customers are mostly composed of residential water users. The significant users accounted for approximately 8782.2 m^3d^{-1} water consumption in 2006. Wholesale customers include the cities of Bradenton, Palmetto, Longboat Key, and some regions in Sarasota County to the south. The water demand to wholesale customers is predictable because of the prescribed contracts and supply agreements. The current agreement with city of Bradenton and town of Longboat Key will remain effective through 2030 and the water demands for these two customers are relatively stable at 1892.7 m^3d^{-1} (0.5 million gallons per day) and 9463.5 m^3d^{-1} (2.5 million gallons per day), respectively. The contract with city of Palmetto expires on September 30, 2019 and is expected to be renewed until September, 2029. After that, a new contract is assumed to be ratified. The agreement for supplying portable water for city of Palmetto is gradually increasing based on each five-year basis. Current agreement with Sarasota Country will expire after 2020. According to the agreement, the water supplying to Sarasota Country will gradually decreasing based on each five-year basis. Table 1-1 lists the detailed amount of water demand for wholesale customers based on annual average flows in m^3 per day. Reserve capacities available to wholesale users are consistent over time as set forth in fixed agreements.

Table 1-1 Water demand projections for wholesale customers in terms of annual average flows (Board of Country Commissioner, 2008)

Wholesale Customers	**2006**	**2010**	**2015**	**2020**	**2025**	**2030**
City of Bradenton	1,892.7	1,892.7	1,892.7	1,892.7	1,892.7	1,892.7
City of Palmetto	7,570.8	7,570.8	9,463.5	10,409.9	11,356.2	12,113.3
Town of Longboat Key	9,463.5	9,463.5	9,463.5	9,463.5	9,463.5	9,463.5
Sarasota County	37,854.1	30,283.3	22,712.5	18,927.1	0	0

Unit: m^3d^{-1}

Water demand to retail customers and significant users in the future is generally unknown and not easy to predict because of the natural of uncertainty existed in the system. The Manatee County Planning Department developed detailed population projections, in which adequate historical data of population was required. Future water supply needs is determined based on water usage per capita basis so that the anticipated increase in population will result in an increase in water demand within the Manatee County Utility Department (MCUD) service area. The data for water usage per capita is determined by either arbitrarily setting from target service level (maximum per capita potable water usage) or historical data. Table 1-2 lists the detailed amount of water demand for retail customers and significant users. Thus, the municipal water demand for MCUD is determined by adding the demand of all its users.

Table 1-2 Water demand projections for retail and significant users in terms of annual average flows (Board of Country Commissioner, 2008)

Customers	2006	2010	2015	2020	2025	2030
Retail customers	115,455.1	115,303,6	132,186.6	149,864.5	168,299.4	187,605.0
Significant customers	8,782.2	14,346.7	16,466.5	18,662.1	20,933.3	23,356.0

Unit: m^3d^{-1}

The county-wide water demand in 2006 was 181,018.4 m^3d^{-1} (47.82 million gallons per day), including 115,455.1 m^3d^{-1} (30.5 million gallons per day) for domestic water usage, 65,563.3 m^3d^{-1} (17.32 million gallons per day) for wholesale customers and significant users. Wi It is projected (Board of Country Commissioner, 2008) that the yearly average portable water demand will increase to an estimated 234,317.0 m^3d^{-1} (61.93 million gallons per day) by year 2030 based on the projected population increase. Currently the county has a sufficient permitted water supply to meet the projected water demand by in 2014. Thus, expansion of current water system facilities is required to meet the year-2030 water supply goal as the supply and demand will likely become imbalanced by the year 2014. The water supply shortage by the year 2030 is projected to be 34,447.2 m^3d^{-1} (9.1 million gallons per day).

1.2.4 Future Water Supply Alternatives

MCUD identified twenty potential water supply alternatives from a combination of surface water and groundwater sources in order to meet the increasing water demand. They are grouped into five categories: groundwater options, surface water options, water right transfer options, regional water options, and other options.

Groundwater options include building new wellfields in various locations of Manatee County identified as a part of the MARS projects. Because of the MARS system with less groundwater for irrigation, MCUD is able to increase permitted groundwater pumping by allocation for potable water supply. The MARS projects consist of four phases: MARS-I, MARS-II, MARS-III, and MARS-IV, among which MARS-I and MARS-II projects have been implemented.

Surface water options refer to those alternatives for new or expansion of existing reservoirs, by which additional surface water can be diverted from rivers into the reservoirs during wet seasons. Some of the surface water may be used for irrigation purposes without treatment at Manatee WTP. This amount is then counted as groundwater credits for MARS-I expansion while the expansion of MARS-III and IV are unknown. Groundwater credit may be reserved for MARS-I expansion if it can be replaced with surface water sources.

Water right transfer options are to purchase water credits from users who own water use permits but no longer need them. For example, those users may sell their land but they still own the water use permits. Thus, those water use permits can be purchased as water supply sources and transferred for potable water delivery. New water supply alternatives from this group may not be necessarily required to build additional facilities except piping and pumping costs for water distribution.

The concept of regional water supply in this case study was developed by the Peace River Manasota Regional Water Supply Authority (PR/MRWSA), an independent special district and a regional water supply authority created by an interlocal agreement in 1982 under the laws of the

State of Florida. The PR/MRWSA aims to integrate and better manage the water resources in Charlotte County, DeSoto County, Manatee County and Sarasota County so as to provide the region with a sufficient water supply that is reliable, sustainable and protective of the natural resources now and into the future. Starting from 2014, the PR/MRWSA will begin providing water to Manatee County.

The other water options include swamp restoration in Flatford Swamp located in the southeastern portion of Manatee County and seawater desalination. In Flatford Swamp, the excess water is resulted from a significant amount of irrigation runoffs resulting in deaths for many trees. Removing the excess irrigation water from the swamp is predicted to have a positive environmental impact by allowing hardwood trees to re-establish. Seawater desalination is an option to build seawater treatment plant at Tampa Bay site and take advantage of unlimited raw seawater water supply. The disadvantage of this option is the high construction, high operation and maintenance costs.

Brief descriptions of the twenty future water supply alternatives are grouped and summarized in Table 1-3. More detailed information about each of the twenty options can be found in Manatee County water supply facilities work plan released in 2008 (Board of Country Commissioner, 2008).

Table 1-3 The Delineation of Twenty Water Supply Expansion Alternatives in the Future

#	Name of Alternative	Brief Description
Ground Water Options		
1	MARS-I	This option is to supply new groundwater by developing a new wellfield in central Duette Park area near the existing ECWF-1.
2	MARS-II	This option is to supply new groundwater by developing a new wellfield in Erle Road Tank site.
3	MARS-III	These options are to supply new groundwater by developing a new wellfield. The location of the new wellfield has not yet been decided.
4	MARS-IV	

#	Name of Alternative	Brief Description
Surface Water Options		
5	Lake Parrish Reservoir	This option is to divert more surface water from the Little Manatee River in to the existing Lake Parrish Reservoir located in the northern part of Manatee County as a cooling pond for a power plant. The increased water storage in the Lake Parrish Reservoir is used for irrigation purpose to obtain well credits. Improvements on the existing systems include upgrading diversion pumps and distribution pumping and piping facilities.
6	Dredging of Lake Manatee	This option is in an attempt to increase the storage of the Lake Manatee Reservoir so as to increase the surface water annual yield from Lake Manatee. The capital investment includes creation and maintenance of new reservoir and dam, wetlands mitigation costs, and water transmission and treatment at the existing water treatment plant. This alternative may or may not be funded by SWFWMD.
7	Gilley Creek Reservoir	This option is to build a new reservoir upstream of Lake Manatee at the Gilley Creek location so as to yield more annual surface water. This alternative may or may not be funded by SWFWMD.
8	North and East Fork Reservoir	This option is to create an upstream impoundment at the North and East Fork locations to increase storage and yield available at the Lake Manatee intake. The capital investment includes creation and maintenance of new reservoir and dam, wetlands mitigation costs, and water transmission and treatment at the existing water treatment plant. This alternative may or may not be funded by SWFWMD.
9	Tatum Reservoir – Lake Manatee WTP	This option is to develop a reservoir to store surface water diverted from the Myakka River located in the southeastern portion of Manatee County. The stored surface water due to the Tatum Reservoir is used for irrigation purposes so that the well credits that are originally used for irrigation can be transferred for potable water supply. The facilities to be built include an impoundment structure and distribution pumping and piping.
Transferred Water Use Permit Options		
10	Well Credit from Current Reuse Customers	This option is to renegotiate with the current reclaimed water customers for increased reclaimed water flows in the new agreement term. The cost associated with this alternative is to pumping to and treatment at the existing water treatment plant.
11	Developer Provided Water Use Permits (WUP) Transfer	The option is to implement a policy that will require new farmland developers to obtain the previous landowner's water use permit as a part of a land purchase. In this way, MCUD can take off the burden of increasing the water supply to the new potable water demand of new developers.
12	Direct Purchased of WUP	This option is to buy water use permits from permittees who are discontinuing farming operations instead of making new developers purchase the water use permit. This alternative

#	Name of Alternative	Brief Description
		conflicts with option #11 and Manatee County wishes to forego the option if option #11 can be implemented.
Regional Water Options		
13	Peace River Water Treatment Facility Expansion	This option is to improve the existing Pease River water treatment facility in Desoto County by construction of a new 6.0 billion gallon reservoir and expansion water treatment facility's production capacity from 12 to 24 and finally to 48 million gallons per day.
14	Shell Creek Restoration	This option is based on improvements on the existing Shell Creek water system by restoration and enhancement of natural water storage areas. This alternative is for potable water supply to the City of Punta Gorda and the region. An environment benefit is identified for this alternative due to restoration of natural conditions.
15	Dona Bay/Cow Pen Slough Restoration (Option A)	This option is to build a surface new water supply system located within Sarasota County. Dona Bay option A is a two-phase project. The first phase is to build a new reservoir and a new water treatment plant at the Dona Bay site and the second phase is to expand the size and capacity of the reservoir and the water treatment plant.
16	Dona Bay/Cow Pen Slough Restoration (Option B)	This option is to build a new surface water supply system located within Sarasota County. Dona Bay option B is a single phase project. This alternative conflicts with option #15.
17	Flatford Swamp Restoration	This option is to build a new water supply system at Flatford Swamp area located in the southeastern portion of Manatee County. The water source comes from the excess irrigation run-off in Flatford Swamp which causes widespread tree mortality. This alternative conflicts with options #18 and #19.
Other Options		
18	Flatford Swamp – Stored and Treated at Tatum Reservoir	This option is to pump the surplus water stored in the Flatford Swamp which is located in southeastern portion of Manatee County immediately north of Myakka City to the Tatum Reservoir for storage and to build a new water treatment plant to treat the water to potable water standards at the Tatum Reservoir site. This alternative conflicts with options #9, #17 and #19. This alternative may or may not be funded by SWFWMD.
19	Flatford Swamp supplemented with Diversion from the Myakka River – Stored and Treated at Tatum Reservoir	This option is similar to option #18. The difference is that this option will divert seasonal surface water from the Myakka River to supplement the Flatford Swamp irrigation runoff. Diversion structure, pumping facilities and additional capacity of the new water treatment plant will be needed. This alternative conflicts with option #9, #17 and #18. This alternative may or may not be funded by SWFWMD.
20	Seawater Desalination	This option is to treat seawater to potable water standards. New seawater desalination facilities at the Port Manatee site need to be

#	Name of Alternative	Brief Description
		built. High operation and maintenance costs may be experienced. But potential price reduction equipments and funding from SWFWMD may make this alternative a competitive one.

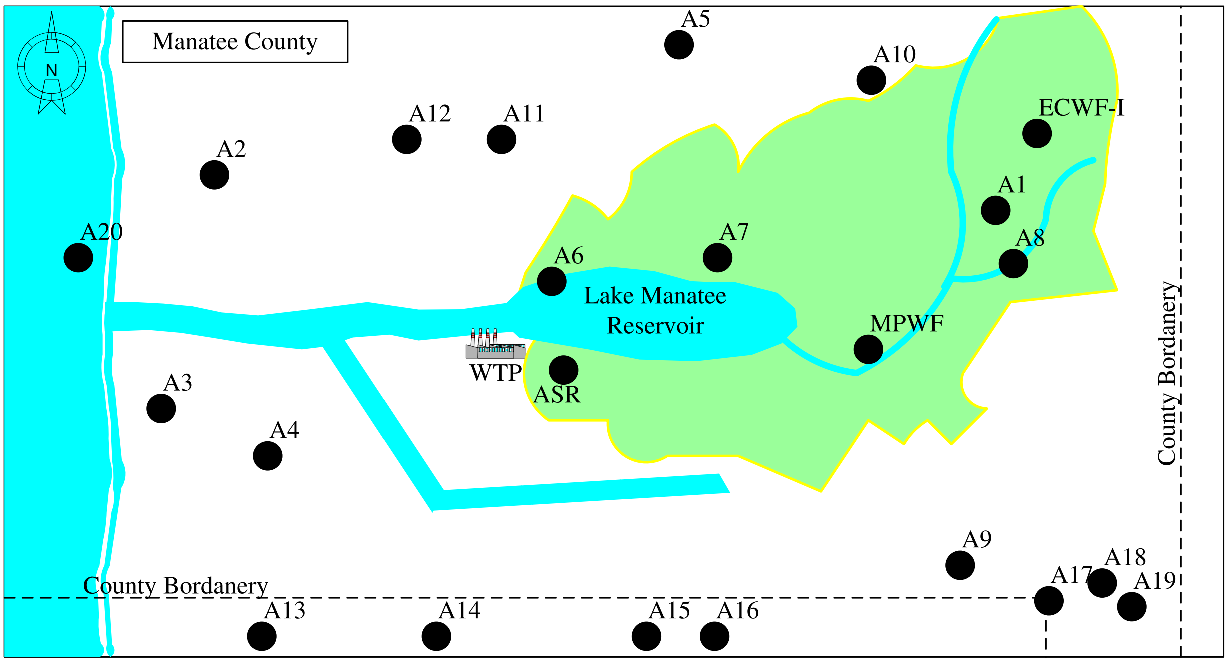


Figure 1-3 Locations of the twenty potential water supply alternatives

The symbolic diagram in Figure 1-3 the locations of all the twenty potential water supply alternatives for the convenience of discussion of optimal expansion strategies. Among them, locations of alternatives 10, 11 and 12 are shown there only for the purposes of illustration because these three alternatives are not required to build any physical facilities. Some of the abovementioned twenty alternatives may be eligible for SWFWMD funding; this potentially lowers their capital investments and hence, decreases the unit cost of finished potable water. However, the SWFWMD funding is not guaranteed even if all required criteria are met, for which uncertainty does exist. In our modeling analysis, we used the highest (conservative) unit cost in alternative evaluation following common practice of engineering feasibility analysis. A summary of the maximal water credit and unit cost for each of the 20 water supply alternatives is shown in Table 1-4 (Board of County Commissioner, 2008). The maximum water credit is defined as the maximum permitted water withdrawal from the water supply expansion alternative. Unit cost, calculated as the present value for a cubic meter or a tonne (t, thereafter) of water in U.S. dollars of 2007, includes the amortization of the estimated initial capital investments and operation and maintenance (O&M) costs.

Table 1-4 Maximum water credit and unit cost of the twenty water supply alternatives

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Max Water Credit	8.21	11.36	7.57	18.93	15.52	44.29	34.83	40.13	17.79	17.03
Unit Cost	0.34	0.53	0.31	0.50	0.51	1.09	0.67	0.74	1.08	0.50
	11	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**
Max Water Credit	0*	0*	45.42	75.71	75.71	75.71	56.78	30.28	43.15	37.85
Unit Cost	0.53	0.60	0.30	0.51	0.76	0.62	0.72	0.61	0.55	1.07

Max Water Credit: 1,000 $m^3 d^{-1}$ Unit Cost: \$ m^{-3}

Note: (*) The max water credits for alternative #10 and #11 are not available. Thus, we set their value of 0 as default.

Sources: Manatee County Water Supply Facilities Work Plan, 2008 (Board of County Commissioner, 2008)

1.3 Research Objectives And Challenges

The system analysis on the water system in this research framework consists of water demand analysis, global climate change evaluation, system optimization on water facilities expansion strategies and decision support under uncertainties. Each module of the water system analysis is interacted with the other as it is illustrated in Figure 1-4. This section defines the research objectives, questions and challenges for each module of the water system analysis (see Figure 1-5).

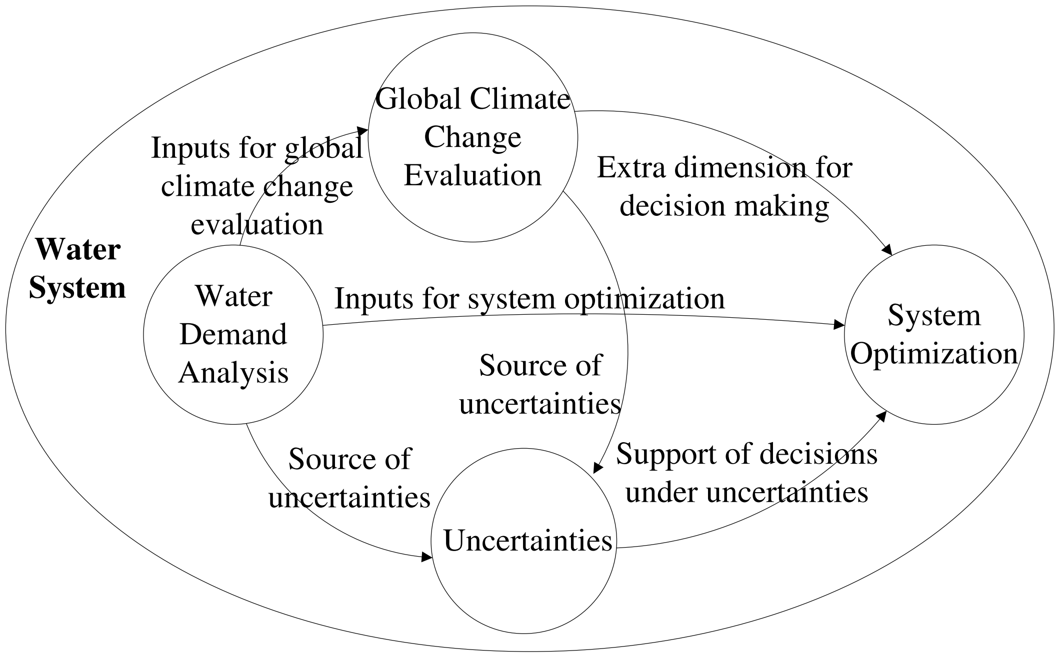


Figure 1-4 System analysis in water system

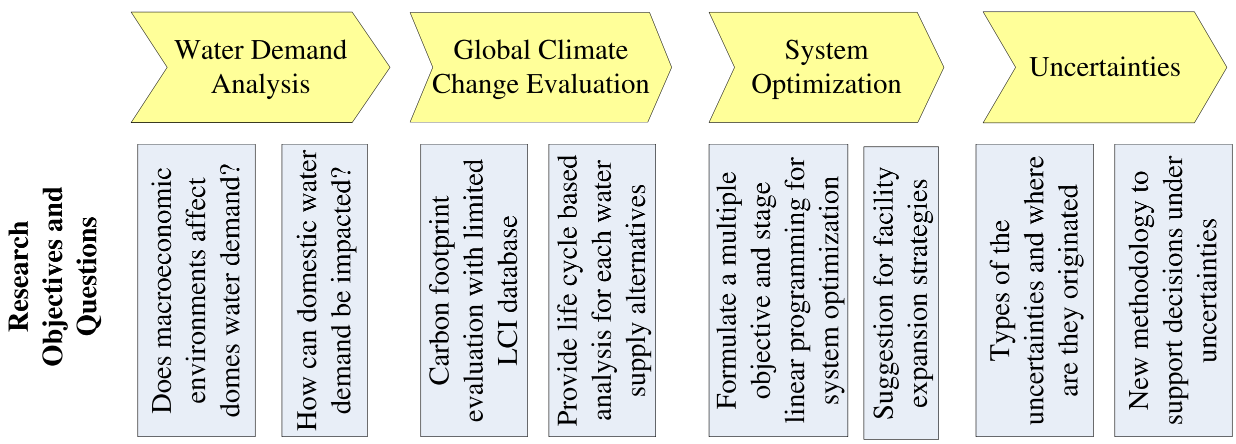


Figure 1-5 Research objectives and questions

1.3.1 Water Demand Analysis

The comparative plots between the historical trend of domestic water demand and previously estimated demand by Manatee County can be presented as the background information at first (Figure 1-6). The estimated demand by Manatee County (Board of Country

Commissioner, 2008), which is based on the assumption of fixed value of per capita demand, is obviously not pleasing. In fact, a various number of macroeconomic factors may affect the per capita values such as unemployment rate and average annual income. The changing pattern of water demand also shows the Florida unemployment rate reflecting the most recent recession cycle from 2003 to 2009. When the unemployment rate declines to the bottom in 2006 and continues to rise until 2009 due to the well-known sub-prime economic crisis, the water demand dropped sharply. Furthermore, the annual average wage of all occupations in Florida as indicated by Figure 1-7 is deemed as an influential factor of water demand. It exhibits a mild linear increase over the study period, which shows a seemingly unrelated relationship in association with the sharp increase of water demand after 2004 and then the sharp drop of water demand after 2007. Such an abrupt change implies other factors that impact the water demand mostly. Whether or not the unemployment rate and average annual income, which are deemed as two principal indicators of the changing macroeconomic environments, can interact with other socioeconomic factors and how they are going to impact the domestic water demand in Manatee County are the two key science questions in this study. However, forecasting for the water demand is out of scope of this research due to the lack of long-term water demand data.

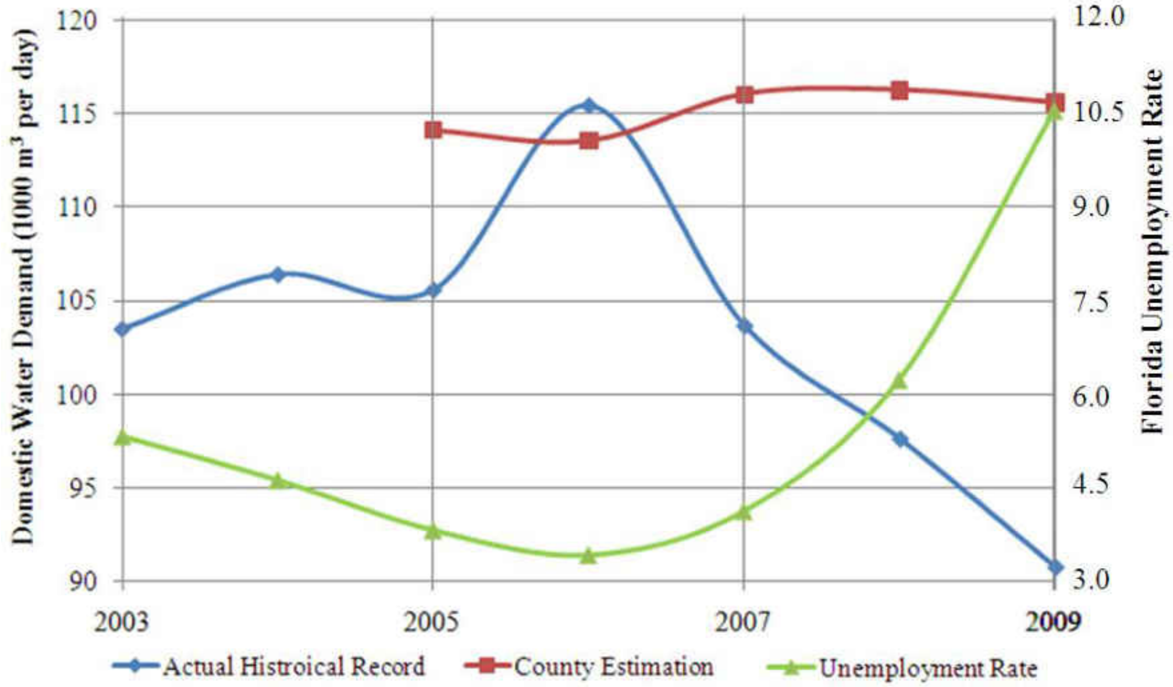
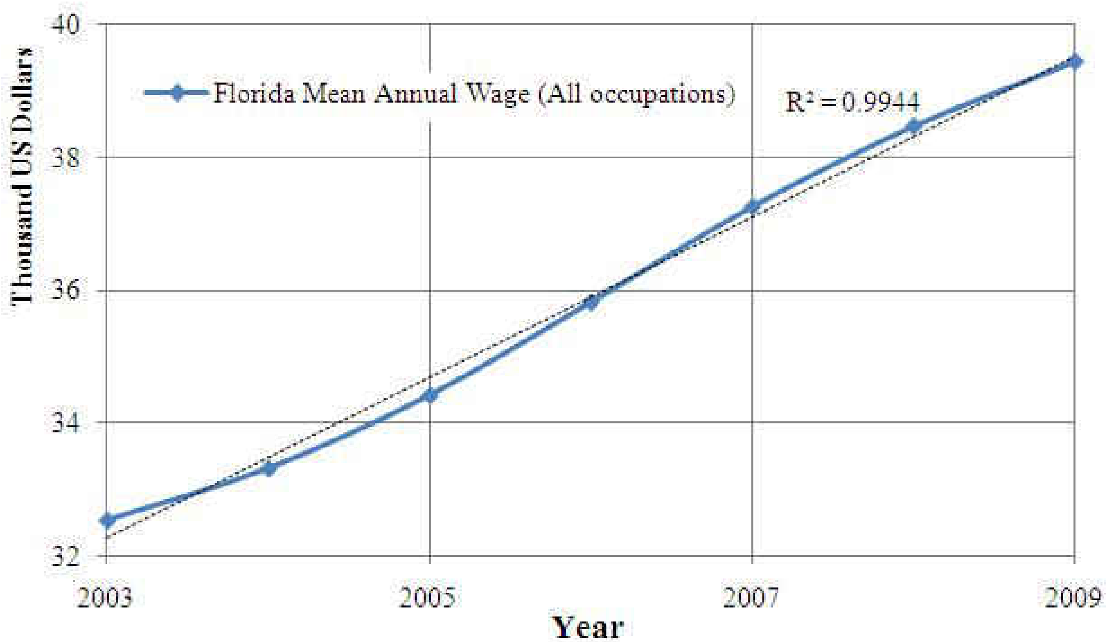


Figure 1-6 Historical domestic water demand, county estimation and unemployment rate



(Source: United States Department of Labor, Bureau of Labor Statistics)

Figure 1-7 Historical Florida mean annual wage (all occupations)

1.3.2 Global Climate Change Evaluation

Over the past decades, cost-effectiveness principle or cost-benefit analysis has been employed oftentimes as a typical assessment tool for the expansion of drinking water utility. With changing public awareness of the inherent linkages between greenhouse gas (GHG) emissions and climate change, the addition of such a new consideration in the assessment regime has altered the landscape of traditional evaluation matrix. However, the global climate change evaluation system for the twenty potential water alternatives is missing from the drinking water infrastructure system in Manatee County, Florida. The global warming potential (GWP) in the entire water production stages (or the entire life cycle) should be quantified with respect to the level of the impacts in units of CO_2 equivalents. It is a challenge in this research to provide an evaluation scheme to quantify the GWP for each of the twenty water alternatives, especially with limited life cycle inventory (LCI) data available, in support of the decision in terms of carbon footprint and cost simultaneously.

1.3.3 System Optimization For Water System Facilities Expansion Strategies

Urban water infrastructure requires careful long-term expansion planning to reduce the risk from climate change during both the periods of economic boom and recession. As part of the adaptation management strategies, capacity expansion in concert with other management alternatives responding to the population dynamics, ecological conservation, and water management policies should be systematically examined to balance the water supply and demand temporally and spatially with different scales. Most current decision-making systems rely on a single attribute such as economic cost. Yet the cost saving itself alone may not reflect all sustainability attributes necessary to evaluate the adequacy of competing water supply expansion options. To mitigate the climate change impact, this practical implementation oftentimes requires carrying out a multi-objective decision analysis by introducing economic efficiencies and carbon-footprint matrices at the same time. The demonstration of the optimal expansion strategies for a typical water infrastructure system in Manatee County, Florida entails the essence of the new philosophy. A full-scale screening and sequencing of multiple competing objectives across a suite of management strategies is needed in this research to cast a possible thrust of the expansion schedule over the next twenty years for the improvement of co-benefits in terms of water infrastructure resilience and low life-cycle cost.

1.3.4 Decision Under Uncertainty

Linear programming is a classic optimization tool for decision makers to derive an optimal solution under the assumption of complete information. The assumption means that all the coefficients and right hand sides in the linear programming model should be perfectly known before a decision can be made. However, most real world problems may violate this assumption due to different types of reasons. Considering the essential uncertainties existing in the study framework, a decision support system under uncertainties is needed. The challenge of in this research is to propose a new methodology to support the decision for a multiobjective linear optimization model in a general form with uncertainties potentially existing anywhere in the model.

1.4 Limitation Of The Research

This research is limited by the nature of the study framework and the availability of information and data. Assumptions and hypothesis are made where needed. However, the methodologies proposed in this research framework are transformative and adaptive to other water infrastructure systems.

CHAPTER TWO: LITERATURE REVIEW

In this section, we review the previous works and techniques that have been developed related to the area in my dissertation.

2.1 Water Demand Modeling

In the past few decades, many approaches were proposed to forecast water demand for both short-term and long-term purposes. Generally, they can be grouped into five categories: the regression analysis, the time series analysis, the computational intelligence approach, the hybrid approach, and the Monte Carlo simulation approach. They are separately described as below.

2.1.1 The Regression Analysis

The regression analysis is based on statistical estimation of the relationship between water demand and explanatory variables (i.e., independent variables) such as socio-economic factors. It assumes that the relationships will continue in the future. The regression analysis approach can then be applied for both short-term and long-term analyses when data are available. For long-term water demand forecasting, the independent variables are usually population and global climate, whereas for short-term water demand forecasting, the independent variables are usually air temperature and rainfall. Some nonlinear regression models were formulated with the inclusion of multiplicative terms as an integral part of the econometric analysis applied for residential and non-residential water demand modeling (Davis, 2003). Four types of models appeared in relation to econometric analysis, including average rate of use, disaggregate factors forecast, functional per unit, and functional population models (Davis, 2003). Table 2-1 summarizes the development of the regression analysis.

Table 2-1 Water demand forecasting based on the regression analysis

	Literatures	Remark	Short Term	Long Term
1960s	Howe and Linaweaver, 1967	Models of residential water demand were structured, with parameters estimated from multi-city cross-sectional data by regression analysis. One of the major findings was that domestic demands were relatively price inelastic.		X
1970s	Cassuto and Ryan, 1979	The study developed a regression model to forecast the residential elasticity of water demand using long-term water conservation programs, revenue, and cost decisions as independent variables in Oakland urban area, California.		X
	Foster and Beattie, 1979	The study presented a generalized model allowing for categorical effects due to regional and size-of-city differences on urban residential water demand		X
1980s	Hughes, 1980	The water demand functions were developed with data from systems varying in size from very small low density rural systems to Salk Lake City's water system. Price of water and outdoor use index were two significant independent variables for short term demand.	X	
	Maidment and Miaou, 1986	Daily water consumption from nine cities in Florida, Pennsylvania and Texas were studied and a regression model was developed to forecast short-term response of daily municipal water use to rainfall and air temperature variations. The overall coefficient of determination R^2 for the nine cities averaged 0.96 in Texas, 0.73 in Florida, and 0.61 in Pennsylvania.	X	
1990s	Billings and Agthe, 1998	This study investigated the regression method and time series state space method and compared them with simple monthly average for short term forecasting of urban water demand in Tucson, Arizona.	X	
2000s	David, 2003	This study investigates four types of econometric models to identify the cumulative effect by using the multiplicative functions.	X	
2000s	Babel et al., 2006	A regression model was developed based on the multivariate econometric approach which considers socio-economic characteristics, climate factors and public water policies and strategies to forecast the domestic water demand.		X

2.1.2 The Time Series Analysis

The approach of time series analysis is based on a statistical breakdown of the various trends that contribute to water demand over time. A time series model may include a long-term trend component, a cyclical component, and a short-term variance component. It is a direct forecasting method without considering other factors such as income and population that water demand may depend on. The time series analysis was extensively used for short-term water demand forecasting in the literature. Table 2-2 summarizes the development of the time series analysis.

Table 2-2 Water demand forecasting based on the time series analysis

	Literatures	Remark	Short Term	Long Term
1980s	Hansen and Narayanan, 1981	A monthly multivariate model was proposed in this study for forecasting water demand. The independent variables include price, average temperature, total precipitation, and percentage of daylight hours.	X	
	Maidment and Parzen, 1984	The approach of the combination of a regression model and time a series analysis was applied for forecasting water use in six Texas cities. In each model, a long-term trend was analyzed by a stepwise regression analysis in terms of population, household income and water price, whereas short-term memory in connection with climatic correlation remains.	X	
	Maidment et al., 1985	A time series model of daily municipal water was developed using the data in Austin, Texas. Rainfall and air temperature were the two independent variables of the model.	X	
	Franklin and Maidment, 1987	The cascade modeling approach was presented to describe weekly water demand based on the data from Deerfield, Florida. The study showed that the inclusion of the autocorrelation term in model considerably improved the forecast accuracy of the weekly data.	X	
	Smith, 1988	A time series model of daily municipal water use was developed in this study. The time series model was termed as a conditional autoregressive process with randomly varying means which accounted for changes	X	

	Literatures	Remark	Short Term	Long Term
		in water use that resulted from price of water, customer income, and many others.		
	Sastri and Valdes, 1989	An iterative computer algorithm that employs a model-switching transfer function was proposed for a time series model which estimated water consumption with rainfall interventions. The method did not need to assume homogeneous and covariance stationary since the transient dropped in the water consumption during rainfall season were removed from time series data.	X	
1990s	Miaou, 1990	A nonlinear monthly time series urban water demand model was proposed using monthly data in Austin, Texas. The performance of the model was compared with conventional linear models. The adjusted R^2 was reported as 0.961.	X	
	Jowitt and Xu, 1992	An approach based on the time series analysis technique was presented. A model using a combination of exponentially weighted mean and autoregressive structures was developed to predict the daily demand.	X	
	Homwongs, 1994	An adaptive smoothing filtering approach for forecasting of hourly municipal water use time series was presented. The seasonal time series model and adaptive forecasting algorithm were based on Winters' exponential smoothing, recursive least squares, and Kalman filter. It can capture both weekday and weekend cycles and produce accurate forecasts from 1h to 24h ahead.	X	
	Molino et al., 1996	A time evolution model of water consumption was proposed in the study for prediction of short-term water demand. Autoregressive moving average model was applied.	X	
2000s	Zhou et al., 2000	A time series model was developed in this study. An autoregressive procedure was used for the short-term variations. Maximum temperature, precipitation and evaporation were climactic variables that account for short-term water consumption. Fourier series was employed to represent long-term seasonal cycle. The model efficiency R^2 was reported as 0.896.	X	X
	Zhou et al., 2002	A time series model was developed for estimation of water demand in 24 hours in advance. The model consisted of long-term trend and short-term variations. The long-term cycle were expressed as a Fourier series and short-term variations were simulated by climatic regression and auto regression. The model efficiency R^2 was reported as 0.75.	X	

Literatures	Remark	Short Term	Long Term
Fullerton et al., 2004	The study created an autoregressive moving average linear transfer function model to study short-term water consumption dynamics in El Paso, Texas. The data used were monthly time series of per-meter water consumption, days with temperature above 90 degree Fahrenheit, rainfall, number of days with rainfall, average real price, and a proxy of income.	X	
Aly and Wanakule, 2004	A short-term forecasting of municipal water use using a deterministic smoothing algorithm was presented. Daily deviations from monthly average were forecasted for up to six days using autocorrelation and weather dependence using six years of daily data. Evaluation in several municipalities near Tampa, Florida showed that the approach provided accurate daily forecasts as measured.	X	
Gato et al., 2007	The study extended the work of Maidment and Miaou, 1986 and Zhou et al., 2000 and proposed a method to calculate temperature and rainfall threshold that would affect the water base use. The new model was tested and yielded an R^2 of 0.81.	X	
Jorge, 2007	The study compared the forecast accuracy of individual and combined univariate time series models (exponential smoothing, autoregressive integrated moving average, and generalized autoregressive conditional) for base use urban water demand modeling for multi-step-ahead water demand forecasting.	X	
Alvisi et al., 2007	A pattern based water demand forecasting model was proposed. The pattern implicit the periodic component in the time series data and daily and hourly demand forecasting module were used to fine tune the estimated values.	X	

2.1.3 The Computational Intelligence Models

The computational intelligence models such as artificial neural networks (ANN), fuzzy-logic model, agent-based model, and so on are based on mathematical models that can be employed for the modeling of complex systems. For example, the ANN models usually consist of at least three layers: input layer, output layer, and the layer in-between or hidden layer. Some complicated ANN models may contain two or more hidden layers. Input layer represents the model inputs, e.g. rainfall and temperature, and output layer represents the model outputs, e.g. water demand. The in-between layer connects these inputs and outputs by a set of highly interconnected nodes and maps the model inputs to the model outputs. The ANN approach is purely data driven, using input date to capture the behavior of a process and forecast output values. An ANN model must be trained using a valid learning algorithm based on historical data. Usually, generated output values are compared with actual values and the errors are propagated backward throughout the ANN to adjust parameters under a supervised or an unsupervised training process. The training process would continue iteratively until an acceptable error rate can be found. The well trained ANN model is then to be used to perform forecasting at a practical level. Table 2-3 summarizes the development of the computational intelligence models.

Table 2-3 Water demand forecasting based on computational intelligence techniques

	Literatures	Remark	Short Term	Long Term
Artificial Neural Networks (ANN)				
2000s	Jain et al., 2001	Two types of ANN models were developed in the study. One consisted only one hidden layer and another one had two hidden layers. Physical variables affecting the process were weekly average maximum air temperature and total weekly rainfall in addition to the water demand records in the past. Conventional modeling method using regression and time serial analysis methods were employed for comparison with the ANN models. The results showed that the ANN model with two hidden layers performed the best.	X	
	Liu et al., 2003	A three-layer ANN was designed in the study to process inputs consisting of water price, house income, and household size in order to generate water demand as an output in Weinan City, China. The model evaluation showed that the correlation coefficients were more than 90% both for the training data and the testing data.	X	X
	Bougadis et al., 2005	The study investigated in cases using ANN models for short-term peak water demand forecasting with respect	X	

Literatures	Remark	Short Term	Long Term
	to rainfall, air temperature and past water demand as input variables. The study compared the results obtained from the ANN models with that from regression models and time series analysis. It showed that the ANN models outperformed the regression models and time-series models.		
Jain and Kumar, 2006	A hybrid neural network models for hydrologic time series forecasting was proposed. The approach was a combination of the conventional and ANN techniques. The results showed that combining the strengths of the conventional and ANN techniques provided a robust modeling framework capable of capturing the non-linear nature of the complex time series and thus produces more accurate forecasts.	X	
Msiza et al., 2007	Artificial neural networks for forecasting both short- and long-term water demand in the Gauteng Province, in the Republic of South Africa were investigated. Two types of neural network architectures, the multi-layer perception (MLP) and the radial basis function (RBF), were used in the study. It was observed that the RBF converges to a solution faster than the MLP	X	X
Ghiassi et al., 2008	The study presented a dynamic architecture for artificial neural networks that was different from traditional back propagation architecture for forecasting urban water demand. It reduced the number of parameters required for model creation and it performed uniformly better than the traditional ANN and auto-regressive integrated moving average method across all time horizons.	X	X
Cutore et al., 2008	A novel application of the Shuffled Complex Evolution Metropolis algorithm (SCEM-UA) for the calibration of an urban water consumption prediction model a daily time scale was proposed. SCEM-UA algorithm was used calibrate the parameters of an ANN model leading to determine the associated parameter and model prediction uncertainties. A comparable predictive capability was obtained compared to the models with classic, deterministic calibration techniques.	X	
Yurdusev et al., 2009	Applicability of feed-forward and radial-basis neural networks for monthly water consumption prediction from several socio-economic and climatic factors affecting water use was investigated. The results indicated that feed-forward and radial methods could	X	

	Literatures	Remark	Short Term	Long Term
		be applied successfully for monthly water consumption prediction.		
Fuzzy Logic Approach				
2000s	Altunkaynak et al., 2005	A fuzzy forecasting model was presented as a function of three consecutive antecedent water consumption amounts in this study for predicting future monthly water demand in Istanbul City using Takagi Sugeno fuzzy method. Being different from regression models and time series analysis methods, this method did not need to assume linearity, normality and independence of residuals.	X	
Agent-based Approach				
2000s	Athanasiadis et al., 2005	The method assigned agents to be water consumers and water-pricing policies makers. With social interactions between agents through an influence diffusion mechanism, communication between agents was implemented. It estimated the water demand in terms of price policies.	X	X

2.1.4 The Hybrid Approach

The hybrid approach is an integrated approach using a few models together to develop synergistic advantages. They can be generally classified as pattern recognition approach, neural-fuzzy approach and the M5 model tree approach. Some advances are reported in the literature in 2000s. Table 2-4 summarizes the hybrid approach.

2.1.5 The Monte Carlo Simulation Approach

Other forecasting models include per-capita-based approach and systems dynamics model can be characterized together because of the inclusion of Monte Carlo simulation approach although not as many reports are found as compared to the forecasting methods in other categories. Table 2-5 summarizes the Monte Carlo simulation approach.

Table 2-4 Water demand forecasting based on the hybrid approaches

	Literatures	Remark	Short Term	Long Term
Patten Recognition Approach				
1990s	Shvartser et al., 1993	A model based on a combination of pattern recognition and time-series analysis was developed in the study to forecast hourly water demand. Three possible daily demand patterns, 'rising', 'oscillating', and 'falling' were defined. The three patterns were defined as states of the demand curve of a Markov process. The transition probabilities were learnt and low-order auto-regressive integrated moving average models fitted using historical data.	X	
Neural-fuzzy Approach				
	Pulido-Calvo and Gutierrez-Estrada, 2007	A hybrid methodology combining feed forward computational neural networks, fuzzy logic and generic algorithm to forecast one-day ahead daily water demand at irrigation districts was presented. The result showed that the hybrid model performed significantly better than univariate and multivariate autoregressive neural networks.	X	
	Wu and Zhou, 2009	A combination model was developed to forecast urban annual water demand. The combination model used Hodrick-Prescott filter method to calculate the trend and cyclical components of the facts that were correlative with water demand and used multiple linear regression method to simulate the trend components. The fuzzy neural network was build based on the cyclical components. All the methods were combined to forecast the urban annual water demand.		X
	Yurdusev et al., 2009	A generalized regression neural network for municipal water consumption prediction was proposed. It was combination of regression analysis and ANN techniques. The results showed that the method could be successfully applied to establish accurate and reliable water consumption prediction models.	X	
M5 Model Tree Approach				
2000s	Solomatine and Xue, 2004	M5 model tree that is a machine learning technique was investigated in a flood forecasting problem for the upper reach of the Huai River in China. M5, ANN and hybrid model forming M5 model tree and ANN were built respectively. The M5 model tree performed similar to ANN models, but faster in training. The hybrid model gave the best prediction result.	X	

Table 2-5 Water demand forecasting based the Monte Carlo simulation approach

	Literatures	Remark	Short Term	Long Term
Per Capita Based Approach with Uncertainties in Global Change				
2000s	Khatri and Vairavamoorthy, 2009	The study presented a method to use Monte Carlo simulation to predict the total future population with uncertainty, using the Latin Hypercube Sampling technique to analysis micro-components of water demand and to get distribution for per capita water consumption. Uncertainties that caused by global climate change were incorporated and climatic variables were assessed using regression models developed from historic records.		X

2.2 System Dynamics Modeling

System dynamics modeling has been used to address practically every sort of feedback system, including business systems (Sterman, 2000), ecological systems (Grant et al., 1997), social-economic systems (Forrester, 1969, 1971; Meadows, 1973), agricultural systems (Qu and Barney, 1998; Saysel et al., 2002), political decision-making systems (Nail et al., 1992), and environmental systems (Vizayakumar and Mohapatra, 1991, 1993; Vezjak et al., 1998; Ford, 1999; Wood and Shelley, 1999; Abbott and Stanley, 1999; Deaton and Winebrake, 2000; Guo et al., 2001). In terms of environmental concerns, the spectrum of application matrix has covered several issues, including environmental impact analysis of coalfields (Vizayakumar and Mohapatra, 1991, 1993), lake eutrophication assessment (Vezjak, 1998), pesticide control (Ford, 1999), wetland metal balance (Wood and Shelley, 1999), groundwater recharge (Abbott and Stanley, 1999), lake watershed management (Guo et al., 2001), river pollution control (Deaton and Winebrake, 2000), and solid waste management (Mashayekhi, 1993; Sudhir et al., 1997; Karavezyris et al., 2002). Within the solid waste management regime, Mashayekhi (1993) explored a dynamic analysis for analyzing the transition in the New York State solid waste system. Sudhir et al., (1997) further employed a system dynamics model to capture the dynamic nature of interactions among the various components in the urban solid waste management system, and Karavezyris et al., (2002) developed a methodology to incorporate qualitative variables such as voluntary recycling participation and regulation impact quantitatively. The model provides a platform for examination of various structural and policy alternatives for sustainable solid waste management. Dyson and Chang (2005) applied the system dynamics modeling to capture the trends of waste generation in a fast growing urban region in Texas. More applications in different topical areas can be found in System Dynamics Review (Abbott and Stanley, 1999). Yet system dynamics model that is able to tackle more complicate interactions among explanatory variables has ever been applied before to handle both long-term and short-term water demand forecasting under uncertainty. In the dissertation, we may use the system dynamics modeling as a tool to forecast future water demand under uncertainty environment.

2.3 Environmental Aspects Of Water System Infrastructures

There is a worldwide concern about the potential effect of climate change on the quality, quantity, timing and demand for water resources. A recent analysis from Natural Resources Defense Council (Natural Resources Defines Council, 2010) shows that climate change will have significant impacts on water supplies in the coming decades, with over 1,100 counties in the 48 contiguous states of USA facing greater risks of water shortages due to the effects of global warming. In particular, decision analysis about water infrastructure expansion in response to such a worldwide concern have long-term implications because the water infrastructure systems we start building today will likely be in place after decades. Very recently, U.S. Environmental Protection Agency (US EPA) started promoting the water infrastructure assessment via developing real world case studies to showcase the successful adaptations projects and to help individual water utilities learn from each other (US EPA, 2009).

Life Cycle Assessment (LCA) is a well-established standard method that can evaluate the environmental impacts of a product, service or project in its entire life period or "from cradle to grave" (ISO 14040, 2006). In the water infrastructure domain, LCA was applied for comparisons among different technical solutions or alternatives in both drinking water supplies (Vince et al., 2007) and wastewater treatment systems (Tillman et al., 1998; Dennison et al., 1998; Lundin et al, 2000; Peters and Lundie, 2001; Hospido et al., 2008; Pasqualino et al., 2011). Harger and Meyer (Harger and Meyer, 1996) developed environmentally sound and sustainable development (ESSD) indicators to measure effects of projects on sustainable development. These indicators, as complementary to LCA, were applied for urban wastewater treatment systems (Parkinson and Butler, 1998; Hellström et al., 2000), agriculture planning (Smith and MacDonald, 1998; Pannell and Glenn, 2000), and urban water supply systems (Lundin and Morrison, 2002). Some analytical frameworks for identifying relevant indicators for assessing the sustainable development were suggested and applied (Hardi et al., 1997; Hodge, 1997; Bagheri and Hjorth, 2007). These studies universally pointed to the difficulty of identifying suitable environmental sustainability indicators (ESIs) applicable to all types of water infrastructure systems.

Carbon footprint is a concise and abstract ESI to characterize the global climate change impact. The carbon footprint is a holistic estimation of the total GHG emissions, being expressed as carbon dioxide (CO_2) equivalents, as a result of a defined action over the project's/product's life cycle or over a specified period of time (Strutt et al., 2008). Thus, CO_2 equivalent is a common metric measure used to compare the emissions from various GHG based upon their GWP. Facing the rising concern of global climate change, the consideration of carbon footprint as a suitable ESI should be meaningful in a carbon regulated environment (e.g. carbon tax or carbon trading) in the future. Such a carbon regulated environment would certainly require the impact of carbon footprints being incorporated into all decision making processes in water infrastructure assessment. It is believed that future water infrastructure assessment in response to climate change must have the carbon footprint included in relevant risk analysis and vulnerability assessment.

A few methodologies which include GWP as one of the dimensions to support a decision marking process have been applied to water supply systems in the literature. An LCA study in the metropolitan area of Sydney, Australia compared future potential scenarios in each of the life cycle impact categories with each other in water systems planning (Lundie et al., 2004). Stokes and Horvath (Stokes and Horvath, 2006) developed an MS-Excel-based decision-support tool, called Water Energy Sustainability Tool (WEST), which considers every phase of the life cycle of water supply systems. Their case study compared the GWP among three possible future water supply alternatives (e.g. imported water, desalinated water, recycled water) in California. Such a tool can be customized for applications in other locations too (Stokes and Horvath, 2009). Friedrich and others conducted a carbon footprint analysis for water supply systems in a South Africa city (Friedrich et al., 2009). In their study, future possible scenarios were compared with the current base case in terms of CO_2 equivalents of GHG emissions.

2.4 Multiobjective Interval Linear Programming With Uncertain Coefficients

Linear programming is a classic optimization tool for decision makers to derive an optimal solution under the assumption of complete information. The assumption means that all the coefficients and right hand sides in the linear programming model should be perfectly known before a decision can be made. However, most real world problems may violate this assumption due to different types of reasons. To name a few examples, a decision may be made by a group of people who may have different recognitions of a problem that results in vagueness of parameters in the problem. Some parameters in a problem can be random variants that may or may not follow some underlying distributions. Or those parameters in a problem are extremely difficult, if not unable, to be obtained so that decision makers are forced to make a decision based on the incomplete information. The classic sensitivity analysis is a post optimality analysis tool that provides ranges for coefficients in the objective function and right hand sides within which the changes are allowed to keep the optimal if only one is changing at a time. For the changes in more than one coefficient in the objective or right hand sides at a time, 100% rule (Bradley et al., 1977) provides a sufficient condition to keep the optimal. These post optimality analysis tools are derived from simplex method and hence can not analyze the uncertainties of coefficients in the constraints because inverse of an uncertain matrix is NP-hard (Coxson, 1999). Furthermore, the post optimality analysis methods can not suggest any other solutions other than the optimal based on the incomplete information. All these are the motivations to the development of linear programming under uncertainties.

Continuous efforts were made by previous researchers to address the uncertainties in single or multiple objective linear programming models. For example, these efforts include studies on the uncertainties only in objectives function (Rommelfanger et al, 1989; Ishihuchi, 1990), only in constraints (Mráz, 1998; Kuchta, 2008), or both (Urli and Nadeau, 1992; Huang et al., 1992; Tong, 1994). Uncertain parameters can be stochastic based on underlying probability distributions, fuzzy numbers based on underlying membership functions or interval numbers that only specify the lower and upper bounds. Stochastic programming (Birge and Louveaus, 1997;

Kall and Wallace, 1994; Ruszczyński and Shapiro, 2003), fuzzy programming (Zimmerman, 1978; Inuiguchi, et al., 1990; Inuiguchi and Ramik, 2000), interval programming (Chinneck and Ramadan, 2000; Oliveira and Antunes, 2007) and combinations of these methods (Liu and Iwamura, 1998; Huang et al., 2001; Nie et al., 2007) were developed to address those uncertainties.

Due to the rich resources available in the literature, it is not the scope of this paper to review all the available approaches. We only focus on single and multiple objective interval linear programming (MOILP) with the following general form, as described in Problem (2-1).

$$\text{Min } Z_p = \sum_{j=1}^{n} c_{pj}^{\pm} x_j \tag{2-1}$$

$$\text{Subject to } \sum_{j=1}^{n} a_{ij}^{\pm} x_j \le b_i^{\pm},\ x_j \ge 0$$

$$i = 1,2,...m,\ j = 1,2,...n,\ p = 1,2,...P$$

The parameters $c_{pj}^{\pm}$, $a_{ij}^{\pm}$ and $b_i^{\pm}$ are interval numbers with their lower and upper bounds known.

So that $c_{pj}^{\pm} \in \{c_{pj} \mid c_{pj}^{-} \le c_{pj} \le c_{pj}^{+}\}$, $a_{ij}^{\pm} \in \{a_{ij} \mid a_{ij}^{-} \le a_{ij} \le a_{ij}^{+}\}$ and $b_i^{\pm} \in \{b_i \mid b_i^{-} \le b_i \le b_i^{+}\}$.

We restrict ourselves to only review the related works and solution approaches to Problem (2-1) in Section 2.4. For techniques in fuzzy linear programming, we refer readers to a comprehensive reference survey (Inuiguchi and Ramik, 2000). For techniques in stochastic linear programming, we refer readers to two books (Birge and Louveaus, 1997; Kall and Wallace, 1994).

The general principle of solving interval linear programming is to transform the uncertain problem into one or more than one deterministic problems with proper rationality or interpretation that can be solved by the classic simplex method. Then, the solutions derived from the deterministic problems are checked whether they can be accepted for the original uncertain problem. The available approaches in the literature for interval linear programming can be briefly categorized into two perspectives. One of the perspectives is to work out a solution set, each element of which is either a potential optimal solution for a single objective linear programming or a Pareto optimal solution for a multiobjective linear programming with the uncertain coefficients given within their admissible ranges of variation. A Pareto optimal solution was also called an efficient solution in some literature (Bitran, 1980; Inuiguchi and Sakawa, 1996). The other perspective is to work out a single optimal solution from the reformulated deterministic problem by incorporating decision maker's goals (such as aspiration level) and preferences (such as utilities) or adopting some certain criteria (such as minimax regret).

2.4.1 Solution Set For Interval Linear Programming

In the first perspective of approaches, a two-step-method (Huang et al., 1992; Huang, 1994) and its similar method (Tong, 1994) were proposed for single objective interval linear programming to find out a possibly optimal solution set. Both of the methods suggested transforming the original interval linear programming into two sub-problems with one of which has the most favorable version of the objective function and the maximum value range inequality and the other one of which has the least favorable version of the objective function and the minimum value range inequality. The maximum and minimum value range inequalities are largest and smallest possible feasible region determined by the non-deterministic constraints (Chinneck and Ramadan, 2000). The derived solutions from these two methods are interval solutions with the expectation to include all possibly optimal solutions. A possibly optimal solution to a single objective interval linear programming problem is an optimal solution to at least one deterministic linear programming problem with the uncertain parameters selected within their admissible ranges of variance. The solution can be obtained fast and thus it is popularly referenced and applied to many real world examples (Maqsood et al., 2005; Cheng et al., 2009; Cao et al., 2010). However, the rationality of the solution to the original interval linear programming is highly doubtable. Here, we refer to the numeric example in (Huang et al., 1992).

$$\begin{aligned} &\text{Max } f = [50,60]x_1 - [70,90]x_2 \\ \text{Subject to } \quad &[4,6]x_1 + x_2 \le 150 \\ &6x_1 + [5,7]x_2 \le 280 \\ &x_1 + [3,4]x_2 \le 90 \\ &[1,2]x_1 - 10x_2 \le -1 \\ &x_1, x_2 \ge 0 \end{aligned} \tag{2-2}$$

The interval solution that is derived from the two-step-method is $x_1 = [24.18, 36.56]$, $x_2 = [3.76, 4.94]$ and $f = [764.71, 1930.73]$. When the interval solution is checked in Problem (2-2), the expectation of including all possible optimal solutions in the interval solution is not satisfied. For illustration, Figure 2-1 plots 10,000 possibly optimal solutions to Problem (2-2), each of which is solved from a deterministic problem with those uncertain coefficients uniformly and independently sampled within their admissible ranges of variance. Apparently, the first issue is that more than half of the possibly optimal solutions in this example are out of the interval solution set which is derived from the two-step-method. Besides, the second issue is that not all the elements in the derived interval solution are possibly optimal solutions. Huang and Cao (Huang and Cao, 2011) later recognized the second issue and proposed a three-step-method, which adds an extra step to the two-step-method to shrink the interval solution set to q ($0<q<1$) level so that all elements in the derived interval solution are possibly optimal. However, that approach makes the first issue even more severe since more possibly optimal solutions become out of coverage of the interval solution set.

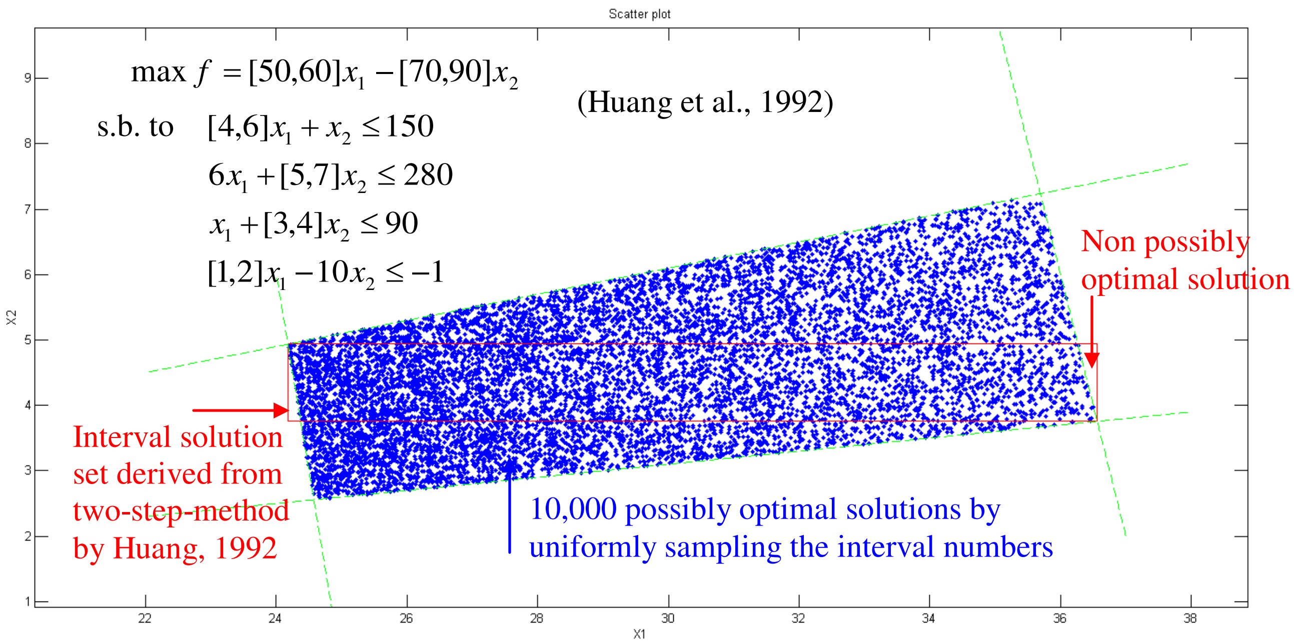


Figure 2-1 An illustration example for two-step-method

Also it is noticed in this example that the true possibly optimal solution set in the solution space is hardly a rectangle-like shape so that it can not be assumed to have an interval solution pattern as $x_{\text{opt}} = [x^{-}_{\text{opt}}, x^{+}_{\text{opt}}]$. More likely, as illustrated in Figure 2-2, the possibly optimal solutions can be dispersed in the solution space. Thus, an interval solution set for an interval linear programming will inevitably cause either the issue of not including all the possibly optimal solutions or the issue of not all the elements in solution are possibly optimal, or both of the issues at the same time. Nevertheless, the minimum and maximum possibly objective values derived from the two-step-method are still valid and proved (Chinneck and Ramadan, 2000).

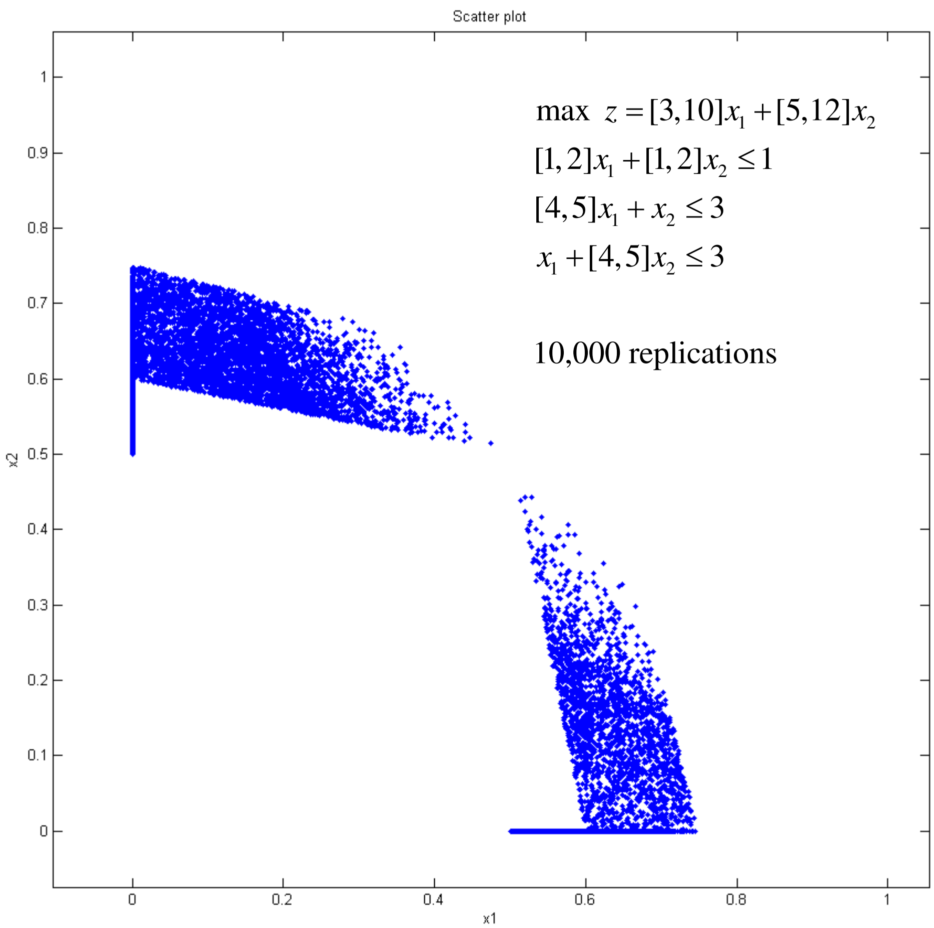


Figure 2-2 Another illustration example of possibly optimal solutions in solution space

For multiobjective linear programming, the optimal solution for all the objective functions usually does not exist. Instead, efforts were made to find Pareto optimal solution (or efficient solution) set. A solution is efficient if there is no other feasible solution available to improve at least one of the objective functions without compromising the others (Zimmermann, 1978). When there are only uncertainties in the objective functions, Bitran (Bitran, 1980) proposed the concepts of necessarily and possibly efficient solution set and provided the test method to determine whether a feasible solution belongs to those sets. A necessarily efficient solution is a feasible solution that is efficient to any deterministic multiobjective linear programming with the uncertain parameters selected with their admissible range of variance. A possibly efficient solution is a feasible solution that is efficient to at least one deterministic multiobjective linear programming with the uncertain parameters selected with their admissible range of variance. The test method was later extended for the uncertain parameters being fuzzy numbers (Inuiguchi and Sakawa, 1996). Also, there were researches available to find necessarily efficient and possibly efficient solution sets (Steuer, 1986; Ida, 2005; Wang and Wang, 2001). However, all these approaches are limited to the cases with certain feasible region. That means, these methods can only be applied to Problem (2-1) when $a_{ij}^- = a_{ij}^+$ and $b_i^- = b_i^+$.

2.4.2 Single Solution For Interval Linear Programming

In the second perspective of approaches, it is focused to find out a single best solution to the decision maker. The single best solution is usually the optimal solution of the reformulated deterministic problem with interpretations from the decision maker's perspective of view. A variety of reformulation methods were proposed in the literature.

For treatment of uncertain constraints, Urli and Nadeau (Urli and Nadeau, 1992) proposed the idea of degree of satisfaction (α) on the non-deterministic constraints (see Figure 2-3). With pre-specified satisfaction thresholds from decision makers, those non-deterministic constraints can be transformed into deterministic constraints.

$$\alpha_i = \begin{cases} 1 & , \sum_{j=1}^{n} a_{ij}^+ x_j \le b_i^- \\ 0 & , \sum_{j=1}^{n} a_{ij}^- x_j \ge b_i^+ \\ \dfrac{b_i^+ - \sum_{j=1}^{n} a_{ij}^- x_j}{b_i^+ - b_i^- + \sum_{j=1}^{n} a_{ij}^+ x_j - \sum_{j=1}^{n} a_{ij}^- x_j} & , \text{elsewhere} \end{cases}$$

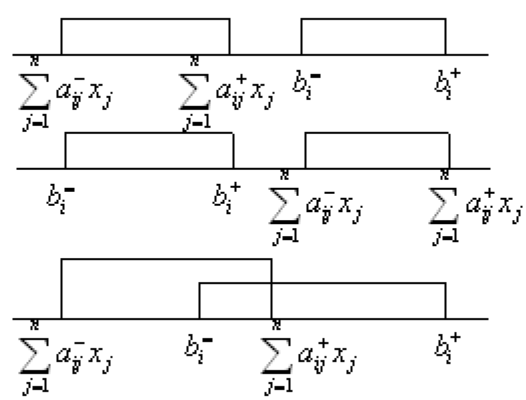


Figure 2-3 Definition of degree of satisfaction of the non-deterministic constraints

Similarly, Sengupta et al. (Sengupta et al., 2001) proposed the acceptability index ($\mathscr{A}$) to evaluate the inferior or superior relation of non-deterministic constraints. The acceptability index determined by the midpoints and half widths of the two interval numbers, or $\mathscr{A}_i = \dfrac{m_i(B) - m_i(A)}{w_i(B) + w_i(A)}$, where $m_i(A) = \dfrac{1}{2}(\sum_{j=1}^{n} a_{ij}^{+} x_j + \sum_{j=1}^{n} a_{ij}^{-} x_j)$, $w_i(A) = \dfrac{1}{2}(\sum_{j=1}^{n} a_{ij}^{+} x_j - \sum_{j=1}^{n} a_{ij}^{-} x_j)$, $m_i(B) = \dfrac{1}{2}(b_i^{+} + b_i^{-})$ and $w_i(B) = \dfrac{1}{2}(b_i^{+} - b_i^{-})$. Although $\mathscr{A}_i$ is defined in a different form, $\mathscr{A}_i = 2\alpha_i - 1$ essentially in case of $\sum_{j=1}^{n} a_{ij}^{+} x_j \geq b_i^{-}$ and $\sum_{j=1}^{n} a_{ij}^{-} x_j \leq b_i^{+}$. The selection of degree of satisfaction or acceptability index reflects the potential risks that decision maker may agree to take to potentially violate the non-deterministic constraints. The higher α or $\mathscr{A}$ values being selected, the lower risks may be tolerated by the decision maker; and vice versa. Some other researchers apply fuzzy logic to interpret the constraints with uncertain right hand sides (Martinson, 1993; Chang et al., 1997). In their studies, interval right hand sides are interpreted as tolerance levels. A membership function (μ) can be defined for each of the uncertain constraints, which equals to 0 if the constraint is strongly violated (e.g. greater than upper bound of right hand side), 1 if it is satisfied in the crisp sense (e.g. less than lower bound of right hand side), and is linearly decreasing from 1 to 0 over the interval right hand side (see Figure 2-4). Apparently, $\mu_i = \alpha_i$ when $a_{ij}^{-} = a_{ij}^{+} = a_{ij}$. In other words, the fuzzy membership function is essentially the same as the degree of satisfaction when only right hand sides are interval numbers even though the fuzzy membership function is interpreting the non-deterministic constraints from a different viewing angle.

$$\mu_i = \begin{cases} 1 & , \sum_{j=1}^{n} a_{ij}x_j \le b_i^- \\ 1 - \dfrac{\sum_{j=1}^{n} a_{ij}x_j - b_i^-}{b_i^+ - b_i^-} & , b_i^- < \sum_{j=1}^{n} a_{ij}x_j \le b_i^+ \\ 0 & , \sum_{j=1}^{n} a_{ij}x_j > b_i^+ \end{cases}$$

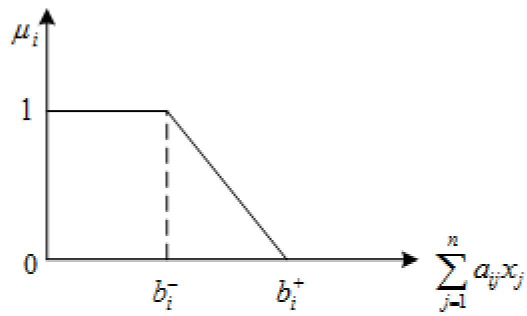


Figure 2-4 Fuzzy membership function for constraint with interval right hand side

In addition, considering a decision has potential risks to violate the uncertain constraints unless the decision is made with restrictions to the minimum value range inequality (Chinneck and Ramadan, 2000), a penalty method was introduced to treat the non-deterministic constraints (Jamison and Lodwick, 2001). In the penalty method, the interval right hand sides are interpreted as resources which can be replenished at a cost that is linear with respect to the amount of violation if the resources are exceeded. In case of replenishments are needed, the occurring costs are subtracted from the objective function as penalties to violate the constraints. The decision makers may specify the penalty terms depending on their preferences or actual costs.

For treatment of objective function with uncertain coefficients, the closed intervals of objective values $[\sum_{j=1}^{n} c_{pj}^- x_j, \sum_{j=1}^{n} c_{pj}^+ x_j]$, $p = 1,2,...P$ can be easily obtained. To transform the objective functions into the whole ranges of the closed intervals, let $Z_p = \lambda_p \sum_{j=1}^{n} c_{pj}^- x_j + (1-\lambda_p)\sum_{j=1}^{n} c_{pj}^+ x_j$, $\lambda_p \in (0,1)$. Or, let $Z_p = \lambda_p \sum_{j=1}^{n} [c_{pj}^- + t_0(c_{pj}^+ - c_{pj}^-)]x_j + (1-\lambda_p)\sum_{j=1}^{n} (c_{pj}^- + t_1(c_{pj}^+ - c_{pj}^-))x_j$, $0 \le t_0 < t_1 \le 1$ for the t_0-and-

t_1-cut of the closed intervals (Chanas and Kuchta, 1996). The λ_p can also be interpreted by decision makers as weights (utilities or preferences) of the best and worst objective values. Since $\lambda_p = 1 - \dfrac{Z_p - \sum_{j=1}^{n} c_{pj}^{-} x_j}{\sum_{j=1}^{n} c_{pj}^{+} x_j - \sum_{j=1}^{n} c_{pj}^{-} x_j} \in (0,1)$, it was also interpreted as aspiration levels by some researchers as shown in Figure 2-5 (Zimmermann, 1978; Chang et al., 1997). The aspiration level is 1 if the objective value is acceptably small (e.g. less than the worst objective value), 0 if the objective value is unacceptably large (e.g. grater than the best object value), and between 0 and 1 for intermediate values (Lodwick and Jamison, 2007). The transformed objective becomes to maximize the aspiration level, which is to maximize λ_p. Apparently, the transformed objective in terms of aspiration level is equivalent to minimize Z_p even though it is interpreted from a different viewing angle.

$$\lambda_p = \begin{cases} 1 & , Z_p \le \sum_{j=1}^{n} c_{pj}^{-} x_j \\ 1 - \dfrac{Z_p - \sum_{j=1}^{n} c_{pj}^{-} x_j}{\sum_{j=1}^{n} c_{pj}^{+} x_j - \sum_{j=1}^{n} c_{pj}^{-} x_j} & , \sum_{j=1}^{n} c_{pj}^{-} x_j < Z_p \le \sum_{j=1}^{n} c_{pj}^{+} x_j \\ 0 & , Z_p > \sum_{j=1}^{n} c_{pj}^{+} x_j \end{cases}$$

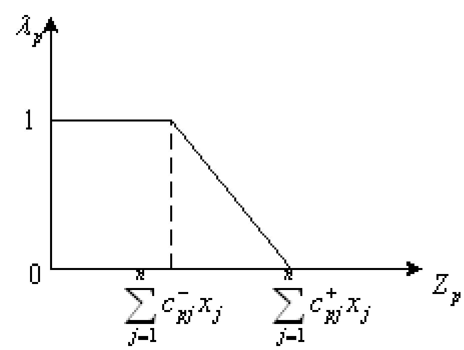


Figure 2-5 Aspiration level for the interval objective functions

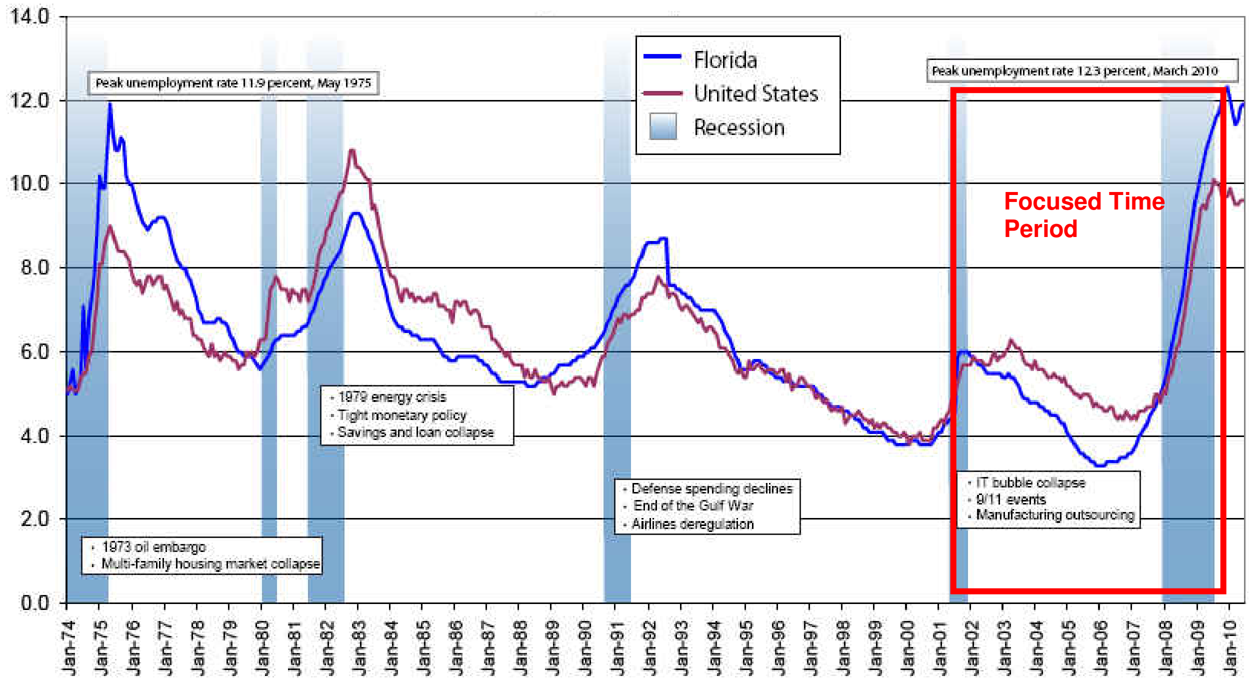
Since the best possible optimal value can only be obtained with restriction to the maximum value range inequality and the least favorable version of objective function (Chinneck and Ramadan, 2000), the best possible optimal value solution always makes λ_p be conflicting with α_i, $\mathscr{A}_i$ or μ_i. As a compromising among all these decision makers' preferences, utilities or attitudes, the maxmini operator was proposed to maximize the minimal level of satisfaction or aspiration of all the λ_p and α_i, $\mathscr{A}_i$ or μ_i (Zimmermann, 1978). The solution obtained by the maxmini approach is usually a single optimal solution. However, in case of potential multiple optimums, an augmented maxmini approach (Lai and Hwang, 1993) may guarantee the obtained optimal solution is an efficient solution which is not dominated by other potential solutions with the same minimal level of satisfaction.

Another criterion that is often considered by decision makers is the worst regret criterion. The regret is caused by uncertainties. When being forced to make a decision under uncertainties, a decision maker may feel regret afterwards knowing that the objective can be better achieved with the uncertainties being known after the decision. Minimizing the worst regret is one of the possible conservative attitudes for decision makers facing uncertainties. The minimax regret approach is a solution method to find out a single best solution which makes the worst regret minimal by calculating the regrets to all possible scenarios after that decision. Some minimax regret optimization in real world applications were available in the literature, for example in municipal solid waste management (Li and Huang, 2006; Chang and Davila, 2007) and energy and environmental systems planning (Li et al., 2012). These studies assume a finite possible scenario set that the decision makers already know before the decision, in case of which the solution can be obtained quickly. However, the major difficulty for the minimax regret approach is that the possible scenario set after a decision may be infinite. For linear programming with interval coefficients in the single objective function, the minimax regret problem can be solved by an iterative relaxation procedure (Shimizu and Aiyoshi, 1980) although it is computational demanding. Inuiguchi and Sakawa (Inuiguchi and Sakawa, 1995) showed that it is sufficient to consider a finite set instead of the infinite set for all possible scenarios of a linear programming with an interval objective function. To further reduce the computational complexity, a heuristic algorithm to the minimax regret solutions was proposed (Mausser and Laguna, 1999). All these approaches only allow interval coefficients in the single objective function.

CHAPTER THREE: METHODOLOGY

3.1 System Dynamics Modeling For Domestic Water Demand Under Changing Economy

Unemployment rate is a well-known indicator in macroeconomic systems, which has been extensively studied (Neftci, 1984; Sichel, 1989; Rothman, 1991). Figure 3-1 is depicted based on Florida and United States labor statistics and recessionary periods, and unemployment rates from Jan. 1974 to Sept. 2010 seasonally adjusted. As shown in Figure 3-1, it is generally believed that unemployment rate has an asymmetric characteristic of fast rising in the recession period and slower falls in the economic recovering period. In particular, Neftci (Neftci, 1984 found some statistical evidence in support of this observation. Although this significant finding of asymmetries was questioned by Sichel (Sichel, 1989) due to an error in Neftci's calculations, Rothman (Rothman, 1991) further strengthened the belief of such asymmetries by using a modified version of Neftci's test and proved that it is statistically significant. Due to such asymmetric property, unemployment rates are highly persistent in the economic recovery period. Such slower recovery from the recession impacts may last for a decade (e.g. from 1982 to 1991 and from 1992 to 2001). In other words, the sudden positive shock to the unemployment rate in year 2008 and 2009 due to the U.S. subprime crisis may propagate trough the future years and take a decade for relief. Thus, a reasonable assumption may be made for the next decade that global economic environment enters the recession recovery period and unemployment rate starts to decline slowly over years. Hence, our system dynamics model particularly in response to the changing correlation between unemployment rate and water demand can be constructed and validated in this research, and out-of-sample estimation can be possibly carried out for future water demand forecasting under the impact of macroeconomic booming and downturn environments alternately.



Source: Florida Agency for Workforce Innovation, Labor Market Statistics Center, Local Area Unemployment Statistics Program, in cooperation with the U.S. Department of Labor, Bureau of Labor Statistics. Prepared October 2010 (seasonally adjusted)

Figure 3-1 Unemployment rates and recessionary periods in Florida and United States

3.1.1 Water Demand Estimation Methodology

The design philosophy of this system dynamics model in which the water demand estimation is driven by the two macroeconomic indicators, namely unemployment rate and average annual income, can be described by Figure 3-2. Such a information flows were fed into the calculations of per capita water demand affected by some independent socioeconomic factors such as population dynamics, real estate market, and net immigrations. The internal linkages between those socioeconomic factors are implicitly established in the upper middle building block supported by both literature values in the past few decades and local historical data from year 2003 to 2009. These internal linkages among those socioeconomic factors may be statistically confirmed by even including interactive and quadratic terms in addition to the first order terms. With the involvement of all these socioeconomic factors which are simultaneously affected with one another, the socioeconomic impact can be well translated to affect the water demand at the county level. With the projected demographic delineation and per capita water demand under the postulated uncertain socioeconomic impact, the domestic water demand in Manatee County can be finally estimated by such a systems dynamic model.

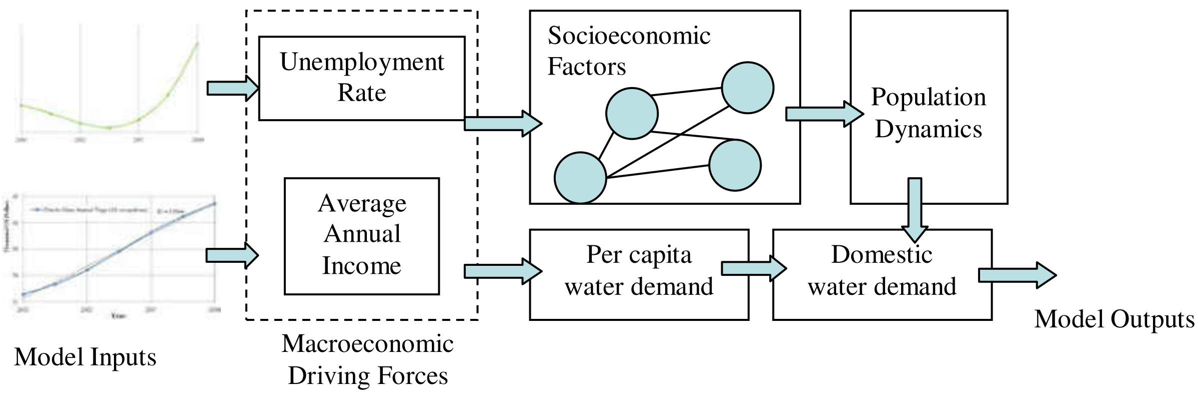


Figure 3-2 System diagram of system dynamic modeling approach

To validate this system dynamics model, model output of the domestic water demand has to be compared with the corresponding historical record. If the goodness of fit criteria may be confirmed, the model is deemed valid and may be used for future water demand forecasting in the next decade based on some assumptions. For example, considering the asymmetric property of the long-term unemployment rate in the business recession cycle, we need to assume that the global economy enters recovery period and the unemployment rate keeps declining in the next decade. Further, since the average annual income presents a significant linearly increasing trend over the years in a full business recession cycle from 2003 to 2009, the linear tendency may be assumed to persist in the future. Therefore, with these two assumptions, future domestic water demand under the impact of the current macroeconomic environment may be possibly forecasted well.

3.2 Carbon Footprint Evaluation For A Water Infrastructure System

The carbon footprint is a sum of CO_2 equivalents in all phases of each expansion alternative. Time duration for this analysis is twenty years from 2011 to 2030 during which the construction, production, use, and recycle phases were analyzed sequentially as shown Figure 3-3. The system diagram shows material and energy flow, where each block represents materials stocks and is connected by arrows with surrounding blocks via essential material flows. Materials, or raw water in our analysis, were initiated from the beginning of a life cycle, passing through intermediate phases and finally sinking in the end of the life cycle. In this analysis, the end-of-life phase of water facilities was not included for the reason that an infrastructure construction usually has a service life over seventy years, a range beyond our focused time period. Besides, a study (Friedrich, 2002) indicated that the overall environmental burden in the end-of-life phase is actually less than 1%. For this reason, a carbon footprint analysis from construction to operation phases in a 20-year time frame (2011-2030) is designed to meet the development goal in Manatee County. To clearly illustrate the processes that are built for carbon footprint calculations in this study, Figure 3-3 lists the system boundaries and assumptions that are made for the estimation of CO_2 equivalents in all relevant phases of 20 expansion alternatives. It is known that the fuel distribution of electric power plants in Manatee and its adjacent counties is a mixture of 53% gas, 24% oil, and 23% coal (as shown in Table 3-2). We therefore adopted this mixed power grid as basis to estimate the carbon footprint associated with each alternative. Only CO_2 equivalent emissions inside the system boundary were included for the calculations of total carbon footprint. Our premise is that the CO_2 calculations for all alternatives are the same in use and recycle phases because there will have no difference in terms of carbon footprints in these two phases given that potable water is to be delivered to consumers by the same way as usual and wastewater is to be collected by the same way for recycling and reuse too. The rest of this section will evaluate the carbon footprint associated with these processes one-by-one in greater details for each alternative. Information and data in the carbon footprint analysis mainly were obtained from the County's work plan. Distances were measured using Google Earth® software. In cases where detailed information (e.g. the amount of fuels and raw materials needed) was not available, assumptions were made with our best judgment.

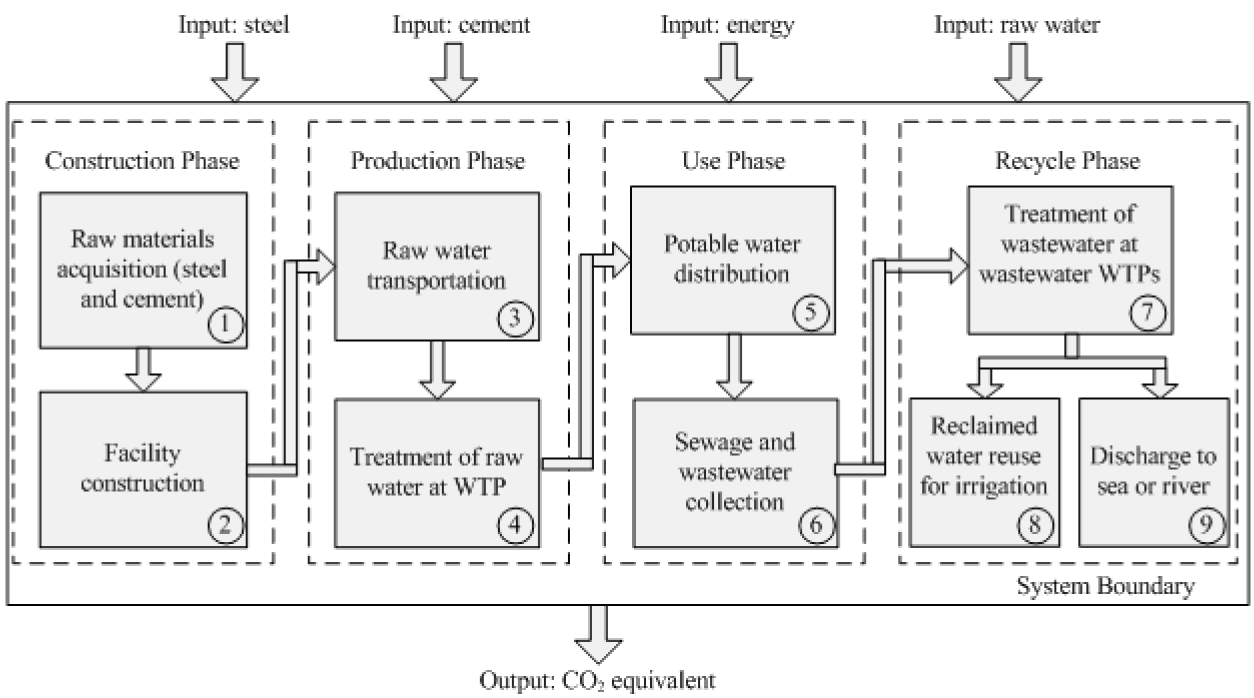


Figure 3-3 System diagram of carbon footprint analysis

Table 3-1 System boundary and associated assumptions in different phases

System boundary and assumptions	
Construction phase: Only raw materials acquisition and facility construction were included in this phase. Transportation of the raw materials to the water infrastructure locations were not considered in this study. We assumed that all raw materials would be obtained locally for construction.	
Process ①	This process only calculated the carbon footprint burden for uses of two major raw

System boundary and assumptions	
	materials (steel and cement) in new WTP construction and pipelines production (steel only). Carbon footprint estimation for earthwork was considered for raw materials required for constructing new reservoirs. Other construction materials were not considered in this study. The carbon footprint estimation only included GHG emissions caused by producing raw materials. Upstream requirements for producing the raw materials (e.g. die cast machine, mixer, etc.) were not considered. Transportation of raw materials was not considered for carbon footprint calculation since both cement and steel plants could be found nearby within our system boundary. It was assumed that the requirements of steel, cement, and earth were proportional to the size and capacity of new facilities.
Process ②	This process only considered the burden of carbon footprint of steel assemblies and concrete-based structural systems. Upstream equipment for the construction of construction tools (e.g., cranes, cement mixers, etc.) was not included for carbon footprint assessment. For all 20 alternatives, we assumed that each square meter of the construction site requires 0.1 m^3 concrete and 0.1 t steel on average.
Production phase: Only raw water treatment and distribution were considered. Some processes related to raw water acquisition were not included in this study. Upstream equipment for plant operation (vessels, controls, etc.) was not considered for this carbon footprint assessment.	
Process ③	Distribution of raw/treated water from the water supply alternative sites to Manatee County WTP was assumed to be essential for all the 20 alternatives even though some alternatives may come with new WTPs. However, it was assumed that treated potable water may depend on the existing piping network for potable water delivery to consumers. The distance between each alternative site and Manatee County WTP was estimated by either actual piping route (e.g. regional water options) measured by Google Earth® or the suggested driving route by Google Map®. Since the study was conducted in relatively flat terrain in southwest Florida USA, a flat topology of pipeline network was assumed for potable water deliveries.
Process ④	We assumed that in terms of carbon footprint, the seawater desalination process was different with the rest of traditional water treatment processes. Thus, the rest of 19 alternatives bore the same burden of carbon footprint in terms of CO_2 equivalents.
Use phase: Only potable water distribution and wastewater collection were considered. The CO_2 equivalent emissions due to using potable water by consumers were not included in this study. The 20 water supply alternatives were assumed to perform by the same way in terms of carbon footprint in this phase.	
Process ⑤	For all the 20 alternatives, we assumed that the delivery of potable water was carried out from the existing Manatee County WTP to the consumers. The delivery distance was estimated by the median distance between the targeted consumers to the WTP. We also assumed that consumers were uniformly distributed in Manatee County. Again, a flat topology of pipeline network was assumed for potable water deliveries.
Process ⑥	This process assumed that the distribution of wastewater to any of the three WWTPs bore the same burden of carbon footprint. The shipping distance was estimated as the median distance from the targeted consumers to one of the three

System boundary and assumptions	
	WWTPs.
Recycle phase: This process did not consider decommission of new facilities and piping network. It only included the consideration of wastewater treatment, and discharge/reuse process. We assumed that there was no difference in terms of carbon footprint over the 20 alternatives in this phase.	
Process ⑦	It was assumed that three WWTPs in Manatee County were identical. Since there was no detailed CO_2 equivalents data available, we assumed that this carbon footprint burden would be similar as the value in the literature.
Process ⑧	It was assumed that transportation of reclaimed wastewater from the WWTPs to the irrigation sites was done by gravity and has no energy consumptions.
Process ⑨	It was assumed that discharge of reclaimed wastewater to sea/river was done by gravity and has no energy consumptions.

Table 3-2 Power generation in Manatee and its adjacent counties

County	Facility Name	MegaWatt	Fuel Type
Hillsborough	TECO Big Bend	1995	Coal
Polk	TECO Polk	693	Coal
Polk	LKLD McIntosh	817	Coal
Manatee	FPL Manatee	1900	Oil
Polk	TECO Polk	940	Oil
Pinellas	Bayboro	232	Oil
Pinellas	Bartow	465	Oil
Hillsborough	Hookers Pt	184	Oil
De Soto	DeSoto	510	Gas
Hardee	van Dolah	680	Gas
Hardee	Hardee	370	Gas
Polk	Seminole	788	Gas
Polk	Tiger Bay	223	Gas
Polk	Peace R	510	Gas
Polk	PEF Hines	1930	Gas
Polk	PPP Mulberry	79	Gas
Polk	OCLP Orange	74	Gas
Polk	LKLD Larsen	153	Gas
Polk	Auburndale Osprey & Peaker	796	Gas
Hillsborough	TECO Bayside	1995	Coal

Source: Florida Department of Environmental Protection, 2010

3.3 Multiobjective Programming For Water System Optimization

Coupled with the methodology in Section 3.2 for carbon footprint quantification, a multiobjective mixed integer programming model is to was formulated for the dynamic assessment of these multi-stage optimal expansion strategies in relation to future water supply scenarios over a 20-year time horizon from 2011 to 2030. Such a compromise programming model can certainly produce the best Pareto frontier solutions of dynamic expansion options. The more the total number of planning periods in such a multi-stage framework, the more the total number of decision variables and parameters to be managed in model simulation. To ease the delineation of the expansion sequence in a streamlined planning horizon, the multistage planning horizon in our decision analysis was divided into four time periods with each one having a 5-year time span. The five year duration is generally feasible for allowing one new alternative to be in place from an engineering perspective if construction is required. Within the trade-off process, one objective is to minimize the total system costs required for the water supply expansion while the other is to minimize the total GHG emissions expressed as CO_2 equivalent. Both are geared toward screening and sequencing relevant water supply alternatives subject to the essential constraints. With a distance-based metrics defined for solving the compromise programming model (Zeleny, 1973), the engineering management questions as to where and when an alternative should be implemented may be answered with a hypothesis that the inclusion of carbon footprints should alter the expansion sequence resulting in the different optimal expansion planning scheme.

3.4 Nested Minimax Regret For Interval Multiobjective Linear Programming

To address the uncertainties in the linear optimization model, we propose a nested minimax regret (NMMR) solution approach which consists of two tiers of the minimax regret solution procedure. In the first tier, minimax regret method is applied to find the single optimal solution in terms of absolute regret for each individual objective and forms a pay-off table. In the second tier, minimax regret method is applied to find a compromising solution in terms of relative regret for all the objectives.

3.4.1 Definition

Problem (2-1) can be rewritten as min $\mathbf{C}^{\pm}\mathbf{X}, \quad \mathbf{X} \in \{\mathbf{X} \,|\, \mathbf{A}^{\pm}\mathbf{X} \le \mathbf{B}^{\pm};\ \mathbf{X} \ge 0\}$, where $\mathbf{X} = (x_1, x_2, ..., x_n)^T$ is the decision vector, $\mathbf{C}^{\pm} = \begin{pmatrix} c_{11}^{\pm} & c_{12}^{\pm} & ... & c_{1n}^{\pm} \\ c_{21}^{\pm} & c_{22}^{\pm} & ... & c_{2n}^{\pm} \\ ... & ... & ... & ... \\ c_{P1}^{\pm} & c_{P2}^{\pm} & ... & c_{Pn}^{\pm} \end{pmatrix}_{P\times n}$ and $\mathbf{A}^{\pm} = \begin{pmatrix} a_{11}^{\pm} & a_{12}^{\pm} & ... & a_{1n}^{\pm} \\ a_{21}^{\pm} & a_{22}^{\pm} & ... & a_{2n}^{\pm} \\ ... & ... & ... & ... \\ a_{m1}^{\pm} & a_{m2}^{\pm} & ... & a_{mn}^{\pm} \end{pmatrix}_{m\times n}$ are the interval matrices for the coefficients in the objective functions and constraints, and $\mathbf{B}^{\pm} = (b_1^{\pm}, b_2^{\pm}, ..., b_m^{\pm})^T$ is the interval column vector for the right hand sides of constraints. Let $\mathbf{X}^* = (x_1^*, x_2^*, ..., x_n^*)^T$ be a decision that is made under the uncertainties of $\mathbf{C}^{\pm}$, $\mathbf{A}^{\pm}$ and $\mathbf{B}^{\pm}$. $\mathbf{C}^* = \begin{pmatrix} c_{11}^{*} & c_{12}^{*} & ... & c_{1n}^{*} \\ c_{21}^{*} & c_{22}^{*} & ... & c_{2n}^{*} \\ ... & ... & ... & ... \\ c_{P1}^{*} & c_{P2}^{*} & ... & c_{Pn}^{*} \end{pmatrix}_{P\times n}$, $\mathbf{A}^* = \begin{pmatrix} a_{11}^{*} & a_{12}^{*} & ... & a_{1n}^{*} \\ a_{21}^{*} & a_{22}^{*} & ... & a_{2n}^{*} \\ ... & ... & ... & ... \\ a_{m1}^{*} & a_{m2}^{*} & ... & a_{mn}^{*} \end{pmatrix}_{m\times n}$, and $\mathbf{B}^* = (b_1^*, b_2^*, ..., b_m^*)^T$ are known after the decision $\mathbf{X}^*$ is made. $\mathbf{C}^*$, $\mathbf{A}^*$ and $\mathbf{B}^*$ are instances of $\mathbf{C}^{\pm}$, $\mathbf{A}^{\pm}$ and $\mathbf{B}^{\pm}$ given that $c_{pj}^* \in \{c_{pj} \,|\, c_{pj}^- \le c_{pj} \le c_{pj}^+\}$, $a_{ij}^* \in \{a_{ij} \,|\, a_{ij}^- \le a_{ij} \le a_{ij}^+\}$ and $b_i^* \in \{b_i \,|\, b_i^- \le b_i \le b_i^+\}$ for all *p*, *i* and *j*. $\{\mathbf{C}^*, \mathbf{A}^*, \mathbf{B}^*\}$ forms one of the unlimited possible scenarios after the decision $\mathbf{X}^*$. We define $\mathbf{R}(\mathbf{C}^*, \mathbf{A}^*, \mathbf{B}^*) = (R_1^*, R_2^*, ..., R_P^*)^T$ as the regret vector, where $R_p^* = \mathbf{C}_p^*\mathbf{X} - \mathbf{C}_p^*\mathbf{X}_{\text{opt1}}^p = \sum_{j=1}^{n} c_{pj}^* x_j^* - \sum_{j=1}^{n} c_{pj}^* x_{pj\,\text{opt}}^*$ is the regret of the *p*-th objective and $\mathbf{X}_{\text{opt1}}^p = (x_{p1_{\text{opt}}}^*, x_{p2_{\text{opt}}}^*, ..., x_{pn_{\text{opt}}}^*)^T$ is the optimal solution for the problem: min $Z_p = \mathbf{C}_p^*\mathbf{X}$,

$\mathbf{X} \in \{\mathbf{X} \mid \mathbf{A}^{*}\mathbf{X} \le \mathbf{B}^{*},\ \mathbf{X} \ge 0\}$. $p = 1,2,...P$. $\mathbf{C}_p^{*}$ is the p-th row vector of $\mathbf{C}^{*}$. We have $R_p = \{\text{all possible } R_p^{*}\text{'s}\}$, $p = 1,2,...P$, which can be an unlimited set.

3.4.2 Nested Minimax Regret Approach

The first tier of the nested minimax regret approach is to find the minimax regret solution for each individual objective function and form a payoff table. That is to solve Problem (3-1)

$$\text{minimax } R_p,\ \mathbf{X} \in \{\mathbf{X} \mid \mathbf{A}^{\pm}\mathbf{X} \le \mathbf{B}^{\pm};\ \mathbf{X} \ge 0\},\ p = 1,2,...P. \qquad (3\text{-}1)$$

R_p can be an unlimited set. Proposition 1 shows that there exists a subset of R_p with a finite number of elements, which is denoted as $\breve{R}_p$, making Problem (3-2) equivalent to Problem (3-1).

$$\text{minimax } \breve{R}_p,\ \mathbf{X} \in \{\mathbf{X} \mid \mathbf{A}^{\pm}\mathbf{X} \le \mathbf{B}^{\pm};\ \mathbf{X} \ge 0\},\ p = 1,2,...P. \qquad (3\text{-}2)$$

where $\breve{R}_p = \{\text{all possible } \hat{R}_p\text{'s}\}$, $\hat{R}_p = \hat{\mathbf{C}}_p\mathbf{X} - \hat{\mathbf{C}}_p\mathbf{X}_{\text{opt3}}^{p}$, $\hat{\mathbf{C}}_p = (\hat{c}_{p1}, \hat{c}_{p2}, ..., \hat{c}_{pn})$,

$\hat{c}_{pj} \in \{c \mid c = c_{pj}^{-} \text{ or } c = c_{pj}^{+}\}$, $j = 1,2,...n$, and $\mathbf{X}_{\text{opt3}}^{p}$ is the optimal solution to problem $\min \hat{\mathbf{C}}_p\mathbf{X},\ \ \mathbf{X} \in \{\mathbf{X} \mid \mathbf{A}^{-}\mathbf{X} \le \mathbf{B}^{+}; \mathbf{X} \ge 0\}$. Apparently, $\|\breve{R}_p\| = 2^{n}$.

Proposition 1: For $\forall\mathbf{C}^{*}$, $\forall\mathbf{A}^{*}$ and $\forall\mathbf{B}^{*}$, there $\exists\hat{\mathbf{C}} = (\hat{c}_{pj})_{P\times n}$, $\mathbf{A}^{-} = (a_{ij}^{-})_{m\times n}$ and $\mathbf{B}^{+} = (b_i^{+})_{m\times 1}$ such that $\mathbf{R}(\mathbf{C}^{*}, \mathbf{A}^{*}, \mathbf{B}^{*}) \le \mathbf{R}(\hat{\mathbf{C}}, \mathbf{A}^{-}, \mathbf{B}^{+})$, where $\hat{c}_{pj} \in \{c \mid c = c_{pj}^{-} \text{ or } c = c_{pj}^{+}\}$.

Proof: Let $\mathbf{R}(\mathbf{C}^{*}, \mathbf{A}^{*}, \mathbf{B}^{*}) = (R_1^{*}, R_2^{*}, ..., R_P^{*})^{T}$, $\mathbf{R}(\hat{\mathbf{C}}, \mathbf{A}^{-}, \mathbf{B}^{+}) = (\hat{R}_1, \hat{R}_2, ..., \hat{R}_P)^{T}$, $\mathbf{C}_p^{*}$ be the p-th row vector of $\mathbf{C}^{*}$, and $\hat{\mathbf{C}}_p$ be the p-th row vector of $\hat{\mathbf{C}}$. $p = 1,2,...P$.

Let $\mathbf{X}_{\text{opt1}}^{p}$ be the optimal solution to $\min \mathbf{C}_p^*\mathbf{X},\ \mathbf{X} \in \{\mathbf{X} \mid \mathbf{A}^*\mathbf{X} \le \mathbf{B}^*; \mathbf{X} \ge 0\}$. For $\forall p$, we have $R_p^* = \mathbf{C}_p^*\mathbf{X} - \mathbf{C}_p^*\mathbf{X}_{\text{opt1}}^{p} = \mathbf{C}_p^*(\mathbf{X} - \mathbf{X}_{\text{opt1}}^{p}) \le \hat{\mathbf{C}}_p(\mathbf{X} - \mathbf{X}_{\text{opt1}}^{p})$, where $\mathbf{X} = (x_1, x_2, ..., x_n)^T$ is decision vector. $\mathbf{X}_{\text{opt1}}^{p} = (x_{1\ \text{opt}}^{p}, x_{2\ \text{opt}}^{p}, ..., x_{n\ \text{opt}}^{p})^T$, $\hat{\mathbf{C}}_p = (\hat{c}_{p1}, \hat{c}_{p2}, ..., \hat{c}_{pn})$, $\hat{c}_{pj} = \begin{cases} c_{pj}^- & , x_j < x_{j\text{opt}}^p \\ c_{pj}^+ & , x_j \ge x_{j\text{opt}}^p \end{cases}$.

$p = 1,2,...P$ and $j = 1,2,...n$.

Let $\mathbf{X}_{\text{opt2}}^{p}$ be the optimal solution to $\min \hat{\mathbf{C}}_p\mathbf{X},\ \ \mathbf{X} \in \{\mathbf{X} \mid \mathbf{A}^*\mathbf{X} \le \mathbf{B}^*; \mathbf{X} \ge 0\}$. For $\forall p$, we have $\hat{\mathbf{C}}_p\mathbf{X}_{\text{opt2}}^{p} \le \hat{\mathbf{C}}_p\mathbf{X}_{\text{opt1}}^{p}$. Therefore, $\hat{\mathbf{C}}_p\mathbf{X} - \hat{\mathbf{C}}_p\mathbf{X}_{\text{opt1}}^{p} \le \hat{\mathbf{C}}_p\mathbf{X} - \hat{\mathbf{C}}_p\mathbf{X}_{\text{opt2}}^{p}$. Thus, we have

$$R_p^* \le \hat{\mathbf{C}}_p(\mathbf{X} - \mathbf{X}_{\text{opt1}}^{p}) = \hat{\mathbf{C}}_p\mathbf{X} - \hat{\mathbf{C}}_p\mathbf{X}_{\text{opt1}}^{p} \le \hat{\mathbf{C}}_p\mathbf{X} - \hat{\mathbf{C}}_p\mathbf{X}_{\text{opt2}}^{p} = \hat{\mathbf{C}}_p(\mathbf{X} - \mathbf{X}_{\text{opt2}}^{p})$$

Let $\mathbf{X}_{\text{opt3}}^{p}$ be the optimal solution to $\min \hat{\mathbf{C}}_p\mathbf{X},\ \ \mathbf{X} \in \{\mathbf{X} \mid \mathbf{A}^-\mathbf{X} \le \mathbf{B}^+; \mathbf{X} \ge 0\}$. Since $\mathbf{X}_{\text{opt2}}^{p} \in \{\mathbf{X} \mid \mathbf{A}^*\mathbf{X} \le \mathbf{B}^*; \mathbf{X} \ge 0\} \subseteq \{\mathbf{X} \mid \mathbf{A}^-\mathbf{X} \le \mathbf{B}^+; \mathbf{X} \ge 0\}$, for $\forall p$, we have $\hat{\mathbf{C}}_p\mathbf{X}_{\text{opt3}}^{p} \le \hat{\mathbf{C}}_p\mathbf{X}_{\text{opt2}}^{p}$. Therefore, $\hat{\mathbf{C}}_p\mathbf{X} - \hat{\mathbf{C}}_p\mathbf{X}_{\text{opt2}}^{p} \le \hat{\mathbf{C}}_p\mathbf{X} - \hat{\mathbf{C}}_p\mathbf{X}_{\text{opt3}}^{p}$. Thus, for $\forall p$, we have $R_p^* \le \hat{\mathbf{C}}_p\mathbf{X} - \hat{\mathbf{C}}_p\mathbf{X}_{\text{opt2}}^{p} \le \hat{\mathbf{C}}_p\mathbf{X} - \hat{\mathbf{C}}_p\mathbf{X}_{\text{opt3}}^{p} = \hat{R}_p$. Hence, $\mathbf{R}(\mathbf{C}^*, \mathbf{A}^*, \mathbf{B}^*) \le \mathbf{R}(\hat{\mathbf{C}}, \mathbf{A}^-, \mathbf{B}^+)$. Proved.

To treat the non-deterministic constraints, we adopt the concept of degree of satisfaction (α) such that the transformed constraints are $\mathbf{A}^+\mathbf{X} - (\mathbf{E} - \boldsymbol{\alpha})(\mathbf{A}^+\mathbf{X} - \mathbf{A}^-\mathbf{X}) \le \mathbf{B}^+ - \boldsymbol{\alpha}(\mathbf{B}^+ - \mathbf{B}^-)$.

$\boldsymbol{\alpha} = \begin{bmatrix} \alpha_1 & & & 0 \\ & \alpha_2 & & \\ & & \cdots & \\ 0 & & & \alpha_m \end{bmatrix}_{m \times m}$ is the degree of satisfaction matrix that decision makers need to specify the for the constraints. $\mathbf{A}^- = (a_{ij}^-)_{m \times n}$, $\mathbf{A}^+ = (a_{ij}^+)_{m \times n}$, $\mathbf{B}^- = (b_i^-)_{m \times 1}$, and $\mathbf{B}^+ = (b_i^+)_{m \times 1}$.

Therefore, the minimax regret method transforms Problem (3-2) to Problem (3-3).

$$\text{minimax } \breve{R}_p, \ \mathbf{X} \in \{\mathbf{X} \mid \mathbf{A}^+\mathbf{X} - (\mathbf{E}-\boldsymbol{\alpha})(\mathbf{A}^+\mathbf{X} - \mathbf{A}^-\mathbf{X}) \le \mathbf{B}^+ - \boldsymbol{\alpha}(\mathbf{B}^+ - \mathbf{B}^-); \ \mathbf{X} \ge 0\} \qquad (3\text{-}3)$$

Let $r_p = \max \breve{R}_p = \max\{\text{all possible } \hat{R}_p\text{'}s\}$ be the maximal regret vector. Problem (3-3) is thus equivalent to Problem (3-4). Apparently, the first tier regrets of a decision are absolute regrets to the objectives.

$$\begin{aligned} &\min \ r_p && (3\text{-}4) \\ \text{Subject to} \quad & r_p \ge \hat{\mathbf{C}}_p\mathbf{X} - \hat{\mathbf{C}}_p\mathbf{X}^p_{\text{opt3}}, \ \text{for all } \hat{\mathbf{C}}_p \\ & \mathbf{A}^+\mathbf{X} - (\mathbf{E}-\boldsymbol{\alpha})(\mathbf{A}^+\mathbf{X} - \mathbf{A}^-\mathbf{X}) \le \mathbf{B}^+ - \boldsymbol{\alpha}(\mathbf{B}^+ - \mathbf{B}^-) \\ & \mathbf{X} \ge 0 \end{aligned}$$

We denote $r_p^{\text{opt}}(\mathbf{X}_p^{\text{opt}}(\boldsymbol{\alpha}), \boldsymbol{\alpha})$ is the optimal objective value to Problem (3-4). $\mathbf{X}_p^{\text{opt}}(\boldsymbol{\alpha})$ is the optimal solution. Proposition 2 shows that $r_p^{\text{opt}}(\mathbf{X}_p^{\text{opt}}(\boldsymbol{\alpha}), \boldsymbol{\alpha})$ is monotone increasing in term of $\boldsymbol{\alpha}$. It provides a guideline for decision makers to specify the $\boldsymbol{\alpha}$-matrix.

Proposition 2: $r_p^{\text{opt}}(\mathbf{X}_p^{\text{opt}}(\boldsymbol{\alpha}_0), \boldsymbol{\alpha}_0) \le r_p^{\text{opt}}(\mathbf{X}_p^{\text{opt}}(\boldsymbol{\alpha}_1), \boldsymbol{\alpha}_1)$ if $\boldsymbol{\alpha}_0 \le \boldsymbol{\alpha}_1$

Proof: Let $\boldsymbol{\Omega}(\boldsymbol{\alpha})$ be the feasible solution space to Problem (3-3). We have $\mathbf{X}_p^{\text{opt}}(\boldsymbol{\alpha}_1) \in \boldsymbol{\Omega}(\boldsymbol{\alpha}_1)$. It is obvious that $\boldsymbol{\Omega}(\boldsymbol{\alpha}_0) \supseteq \boldsymbol{\Omega}(\boldsymbol{\alpha}_1)$ if $\boldsymbol{\alpha}_0 \le \boldsymbol{\alpha}_1$. Thus, $\mathbf{X}_p^{\text{opt}}(\boldsymbol{\alpha}_1) \in \boldsymbol{\Omega}(\boldsymbol{\alpha}_0)$. Therefore, we receive $r_p^{\text{opt}}(\mathbf{X}_p^{\text{opt}}(\boldsymbol{\alpha}_1), \boldsymbol{\alpha}_1) = r_p(\mathbf{X}_p^{\text{opt}}(\boldsymbol{\alpha}_1), \boldsymbol{\alpha}_0) \ge r_p^{\text{opt}}(\mathbf{X}_p^{\text{opt}}(\boldsymbol{\alpha}_0), \boldsymbol{\alpha}_0)$, if $\boldsymbol{\alpha}_0 \le \boldsymbol{\alpha}_1$. Proved.

Therefore, a payoff table can be formed as shown in Table 3-3.

The second tier of the nested minimax regret approach is to find a best compromising solution among all the objectives based on the minimax regret criterion. The regret in the second tier is defined as $\hat{r}_p = \dfrac{r_p(\mathbf{X}(\boldsymbol{\alpha}), \boldsymbol{\alpha}) - r_p^{\text{opt}}(\mathbf{X}_p^{\text{opt}}(\boldsymbol{\alpha}), \boldsymbol{\alpha})}{\max(r_p(\mathbf{X}_p^{\text{opt}}(\boldsymbol{\alpha}), \boldsymbol{\alpha})) - r_p^{\text{opt}}(\mathbf{X}_p^{\text{opt}}(\boldsymbol{\alpha}), \boldsymbol{\alpha})}$, $p = 1,2,...P$, for each of the objectives. Obviously, $\hat{r}_p$ is a scaled value ranging from 0 and 1. Hence, the second tier regrets are relative regrets to the objectives. Let $\breve{r} = \{\hat{r}_1, \hat{r}_2, ..., \hat{r}_P\}$ and $\Gamma = \max \breve{r}$. Thus, the nested minimax regret solution can be obtained by solving Problem (3-5).

Table 3-3 A payoff table for multiple minimax objectives

	r_1	r_2	$\cdots$	r_P
$\mathbf{X}_1^{\text{opt}}(\boldsymbol{\alpha})$	$r_1^{\text{opt}}(\mathbf{X}_1^{\text{opt}}(\boldsymbol{\alpha}), \boldsymbol{\alpha})$	$r_2(\mathbf{X}_1^{\text{opt}}(\boldsymbol{\alpha}), \boldsymbol{\alpha})$	$\cdots$	$r_P(\mathbf{X}_1^{\text{opt}}(\boldsymbol{\alpha}), \boldsymbol{\alpha})$
$\mathbf{X}_2^{\text{opt}}(\boldsymbol{\alpha})$	$r_1(\mathbf{X}_2^{\text{opt}}(\boldsymbol{\alpha}), \boldsymbol{\alpha})$	$r_2^{\text{opt}}(\mathbf{X}_2^{\text{opt}}(\boldsymbol{\alpha}), \boldsymbol{\alpha})$	$\cdots$	$r_P(\mathbf{X}_2^{\text{opt}}(\boldsymbol{\alpha}), \boldsymbol{\alpha})$
$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$
$\mathbf{X}_P^{\text{opt}}(\boldsymbol{\alpha})$	$r_1(\mathbf{X}_P^{\text{opt}}(\boldsymbol{\alpha}), \boldsymbol{\alpha})$	$r_2(\mathbf{X}_P^{\text{opt}}(\boldsymbol{\alpha}), \boldsymbol{\alpha})$	$\cdots$	$r_P^{\text{opt}}(\mathbf{X}_P^{\text{opt}}(\boldsymbol{\alpha}), \boldsymbol{\alpha})$

$$\min \Gamma \tag{3-5}$$

$$\begin{aligned} \text{Subject to} \quad & \Gamma \geq \frac{r_p(\mathbf{X}(\boldsymbol{\alpha}), \boldsymbol{\alpha}) - r_p^{\text{opt}}(\mathbf{X}_p^{\text{opt}}(\boldsymbol{\alpha}), \boldsymbol{\alpha})}{\max(r_p(\mathbf{X}_p^{\text{opt}}(\boldsymbol{\alpha}), \boldsymbol{\alpha})) - r_p^{\text{opt}}(\mathbf{X}_p^{\text{opt}}(\boldsymbol{\alpha}), \boldsymbol{\alpha})}, \quad \text{for all } p \\ & r_p(\mathbf{X}(\boldsymbol{\alpha}), \boldsymbol{\alpha}) \geq \hat{\mathbf{C}}_p \mathbf{X} - \hat{\mathbf{C}}_p \mathbf{X}_{\text{opt3}}^p, \qquad \text{for all } p \text{ and } \hat{\mathbf{C}}_p \\ & \mathbf{A}^+\mathbf{X} - (\mathbf{E} - \boldsymbol{\alpha})(\mathbf{A}^+\mathbf{X} - \mathbf{A}^-\mathbf{X}) \leq \mathbf{B}^+ - \boldsymbol{\alpha}(\mathbf{B}^+ - \mathbf{B}^-) \\ & \mathbf{X} \geq 0 \end{aligned}$$

The scale of Problem (3-5) is determined by the number of objectives (P), number of uncertainties in the objective (n) and the number of constraints (m). Generally, Problem (3-5) is a single objective deterministic linear programming that can be solved by use of the simplex method with $(n + P + 1)$ decision variables and $[p(2^n + 1) + m]$ constraints excluding the non-negativity constraints.

Therefore, the nested minimax regret approach for interval linear programming can be summarized as below:

Step 1: Solve the problems $\min \hat{\mathbf{C}}_p \mathbf{X}$, $\mathbf{X} \in \{\mathbf{X} \mid \mathbf{A}^-\mathbf{X} \leq \mathbf{B}^+; \mathbf{X} \geq 0\}$ and find optimal values.

Step 2: Specify $\boldsymbol{\alpha}$ matrix and solve Problem (3-4) for each individual objective.

Step 3: Form a payoff table as shown in Table 3-3.

Step 4: Solve Problem (3-5) and find the nested minimax regret solution. If the solution is acceptable by decision maker, the obtained solution is the final solution. If not, go to Step 5.

Step 5: Specify a different $\boldsymbol{\alpha}$ matrix and repeat from Step 2 to Step 4.

3.4.3 Numeric Example

We are considering the following multiple objective interval linear programming.

$$
\begin{array}{ll}
\text{Min} & z_1 = [-60,-50]x_1 + [70,90]x_2 \\
\text{Min} & z_2 = [-3,-1]x_1 + [10,20]x_2 \\
\text{Subject to} & [4,6]x_1 + x_2 \le 150 \\
& 6x_1 + [5,7]x_2 \le 280 \\
& x_1 + [3,4]x_2 \le 90 \\
& [1,2]x_1 - 10x_2 \le -1 \\
& x_1, x_2 \ge 0
\end{array}
$$

For simple illustration, we assume the decision makers require equal degree of satisfaction for all the non-deterministic constraints.

Let $\mathbf{C} = \begin{pmatrix} (-60,-50) & (70,90) \\ (-3,-1) & (10,20) \end{pmatrix}$, $\mathbf{A} = \begin{pmatrix} (4,6) & 1 \\ 6 & (5,7) \\ 1 & (3,4) \\ (1,2) & -10 \end{pmatrix}$, $\mathbf{B} = (150,\ 280,\ 90,\ -1)$.

Step 1: Solve the problems $\min \hat{\mathbf{C}}_p \mathbf{X}, \quad \mathbf{X} \in \{\mathbf{X} \mid \mathbf{A}^- \mathbf{X} \le \mathbf{B}^+; \mathbf{X} \ge 0\}$ and find optimal values

z_1		z_2	
$c_{11} = -60$, $c_{12} = 70$	- 1930.7	$c_{21} = -3$, $c_{22} = 10$	- 72.122
$c_{11} = -60$, $c_{12} = 90$	- 1855.6	$c_{21} = -3$, $c_{22} = 20$	- 34.561
$c_{11} = -50$, $c_{12} = 70$	- 1565.1	$c_{21} = -1$, $c_{22} = 10$	1
$c_{11} = -50$, $c_{12} = 90$	- 1490	$c_{21} = -1$, $c_{22} = 20$	2

Step 2: Solve the minimax regret problem for each individual objective and find minimal maximum regret r_1 and r_2 as shown in Figure 3-4.

$$\begin{aligned} &\min \quad r_1 \\ \text{s.t.} \quad & r_1 \geq -60x_1 + 70x_2 + 1930.7 \\ & r_1 \geq -60x_1 + 90x_2 + 1855.6 \\ & r_1 \geq -50x_1 + 70x_2 + 1565.1 \\ & r_1 \geq -50x_1 + 90x_2 + 1490 \\ & \mathbf{A}^+\mathbf{X} - (\mathbf{E} - \boldsymbol{\alpha})(\mathbf{A}^+\mathbf{X} - \mathbf{A}^-\mathbf{X}) \leq \mathbf{B}^+ - \boldsymbol{\alpha}(\mathbf{B}^+ - \mathbf{B}^-) \\ & \mathbf{X} \geq 0 \end{aligned}$$

$$\begin{aligned} &\min \quad r_2 \\ \text{s.t.} \quad & r_2 \geq -3x_1 + 10x_2 + 72.122 \\ & r_2 \geq -3x_1 + 20x_2 + 34.561 \\ & r_2 \geq -x_1 + 10x_2 - 1 \\ & r_2 \geq -x_1 + 20x_2 - 2 \\ & \mathbf{A}^+\mathbf{X} - (\mathbf{E} - \boldsymbol{\alpha})(\mathbf{A}^+\mathbf{X} - \mathbf{A}^-\mathbf{X}) \leq \mathbf{B}^+ - \boldsymbol{\alpha}(\mathbf{B}^+ - \mathbf{B}^-) \\ & \mathbf{X} \geq 0 \end{aligned}$$

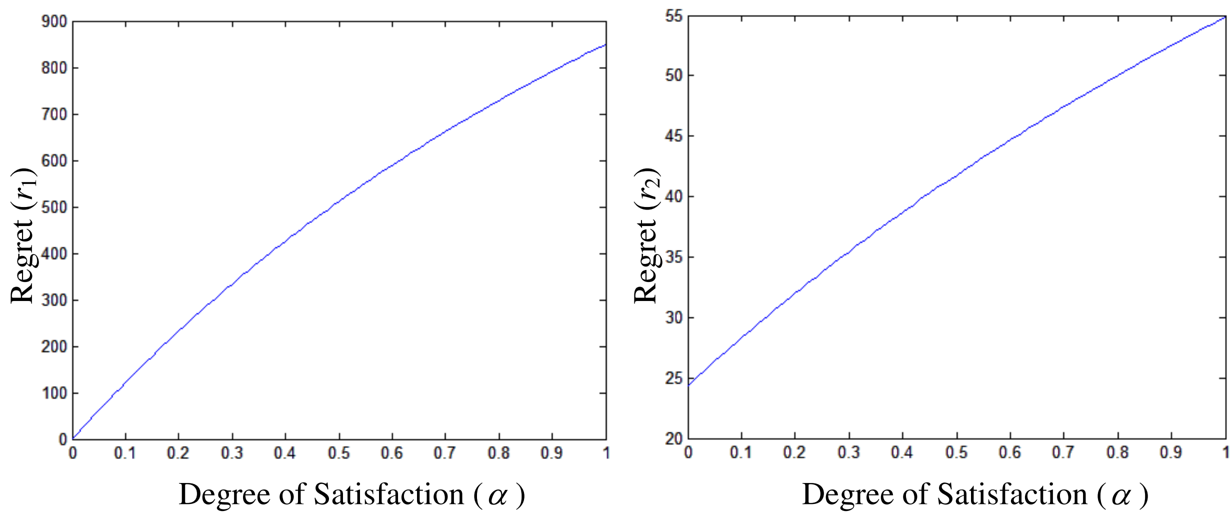


Figure 3-4 The first tier minimax regrets for the two objectives

Assuming the decision maker taking the degree of satisfaction $\alpha = 0.4$, the minimal maximum regret solutions and values for each of the individual objectives are:

$r_1 = 426.3$, $\mathbf{X}_1^{\text{opt}} = (30.344, 4.348)$ and $r_2 = 38.71$, $\mathbf{X}_2^{\text{opt}} = (21.506, 3.111)$.

Step 3: Form a pay-off table

$\alpha = 0.4$	r_1	r_2
(30.344, 4.348)	426.3	54.62
(21.506, 3.111)	858.1	38.71

Step 4: Solve the following problem for the nested minimax regret solution.

$$
\begin{aligned}
& \min \ \Gamma \\
\text{Subject to} \quad & (858.1 - 426.3)\Gamma \geq r_1 - 426.3 \\
& (54.62 - 38.71)\Gamma \geq r_2 - 38.71 \\
& r_1 \geq -60x_1 + 70x_2 + 1930.7 \\
& r_1 \geq -60x_1 + 90x_2 + 1855.6 \\
& r_1 \geq -50x_1 + 70x_2 + 1565.1 \\
& r_1 \geq -50x_1 + 90x_2 + 1490 \\
& r_2 \geq -3x_1 + 10x_2 + 72.122 \\
& r_2 \geq -3x_1 + 20x_2 + 34.561 \\
& r_2 \geq -x_1 + 10x_2 - 1 \\
& r_2 \geq -x_1 + 20x_2 - 2 \\
& 4.8x_1 + x_2 \leq 150 \\
& 6x_1 + 5.8x_2 \leq 280 \\
& x_1 + 3.4x_2 \leq 90 \\
& 1.4x_1 - 10x_2 \leq -1 \\
& x_1, x_2 \geq 0
\end{aligned}
$$

We receive the optimal solution as $\Gamma = 0.4932$, $x_1 = 25.8654$, $x_2 = 3.7212$, $r_1 = 639.2560$, $r_2 = 46.5578$. Select a different α value and repeat from Step 2 to Step 4 if the solution is not accepted by the decision maker. We sweep the α value from 0 to 1 with step size 0.01 and find the nested minimax regret solution for each α by repetitional use of the solution procedure from Step 2 to Step 4. Therefore, the first tier regrets (absolute regrets) and the second tier regret (nested minimax regret) are plotted in terms of α in Figure 3-5.

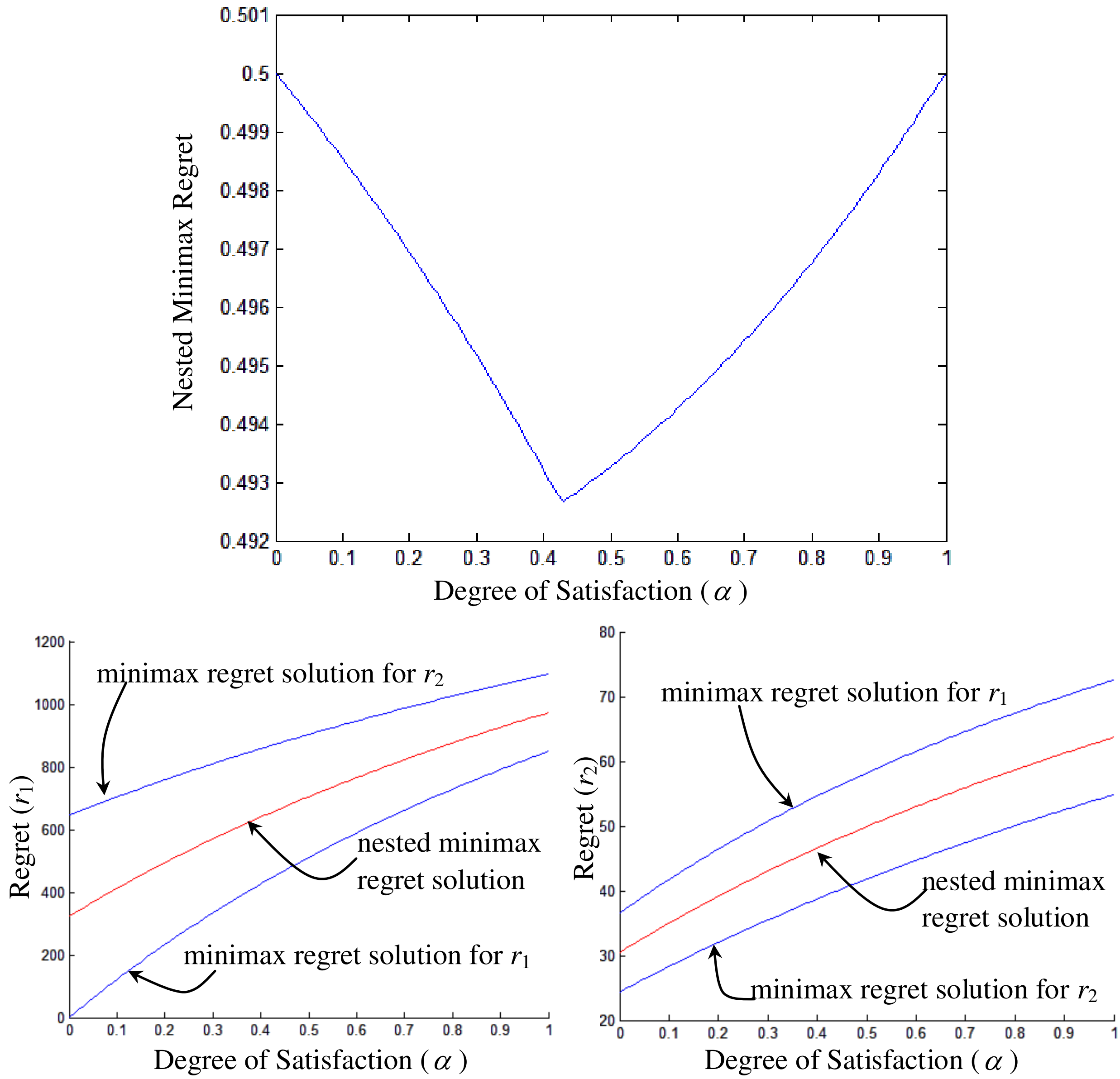


Figure 3-5 Relative and absolute regrets for the nested minimax regret solution

CHAPTER FOUR: MODEL DEVELOPMENT

4.1 System Dynamics Modeling For Domestic Water Demand Under Changing Economy

The system dynamics model used in this study was developed for carrying out the domestic water demand estimation for the Manatee County, Florida in our study period from 2003-2009. At first, it is necessary to create the system diagrams to link all related socioeconomic and managerial components with one another throughout three submodels, including socioeconomic submodel, population dynamics submodel, and water demand forecast submodel. Real world data relevant to various internal linkages among socioeconomic and managerial factors have to be processed to retrieve some regression equations in support of flows and conditions within and between these three submodels. Real world water demand data from 2003 to 2009 can then be used for model validation. Once the system dynamic model can be created and well validated, it would become applicable for future water demand forecasting as the new input data can be generated by other socioeconomic scientists.

4.1.1 Modeling The System Dynamics

In Figure 4-1, the population dynamics was model as a stock being delineated by a number of neighboring components such as the net immigration rate within the submodel. Outside the submodel, however, birth and death rates as well as economic conditions such as unemployment rate and average income may come to play a critical role. With this setting, modeling the water demand in this study became associated with population dynamics and per capita water demand driven by some major relevant socioeconomic factors directly and indirectly. Three submodels are therefore interconnected within the modeling framework. The inputs of unemployment rate and average annual income uniquely reflect the changing macroeconomic conditions from 2003 to 2009 that, in turn, affects the real estate market and other socioeconomic factors in the socioeconomic submodel. Population dynamics submodel is created by using a component method, in which a component of population change per day due to births, deaths, and net migrations is calculated to update the population over years. The component method is also employed by the U.S. Census Bureau for population projections. The difference is that the U.S. Census Bureau employed time series models to estimate the component of population change whereas our system dynamics model entails the intrinsic relationship of these components (mortality, fertility, and net migration) and socio-economic factors integratively and interactively. Given the birth rate, death rate and net migration under the impact of macroeconomic environment, the population dynamic submodel simulates the population growth generating and translating the input data for the water demand forecast submodel where the culminated synthesis of all information flows from socioeconomic and population submodels can be carried over. The water demand forecast submodel, therefore, is defined on a per-capita basis with respect to the per-capita coefficient dynamically updated in association with the changing macroeconomic environments.

The next step is to characterize those intertwined internal linkages within and between these submodels. To carry out the modeling practices, there is a need to quantify the statistical relationships based on all relevant socio-economic and managerial factors as discussed above by fitting regression equations stepwise in support of a suite of legitimate internal linkages in our system dynamics model. Table 4-1 therefore lists all definitions of those socioeconomic factors that were used in the system dynamics model as a summary.

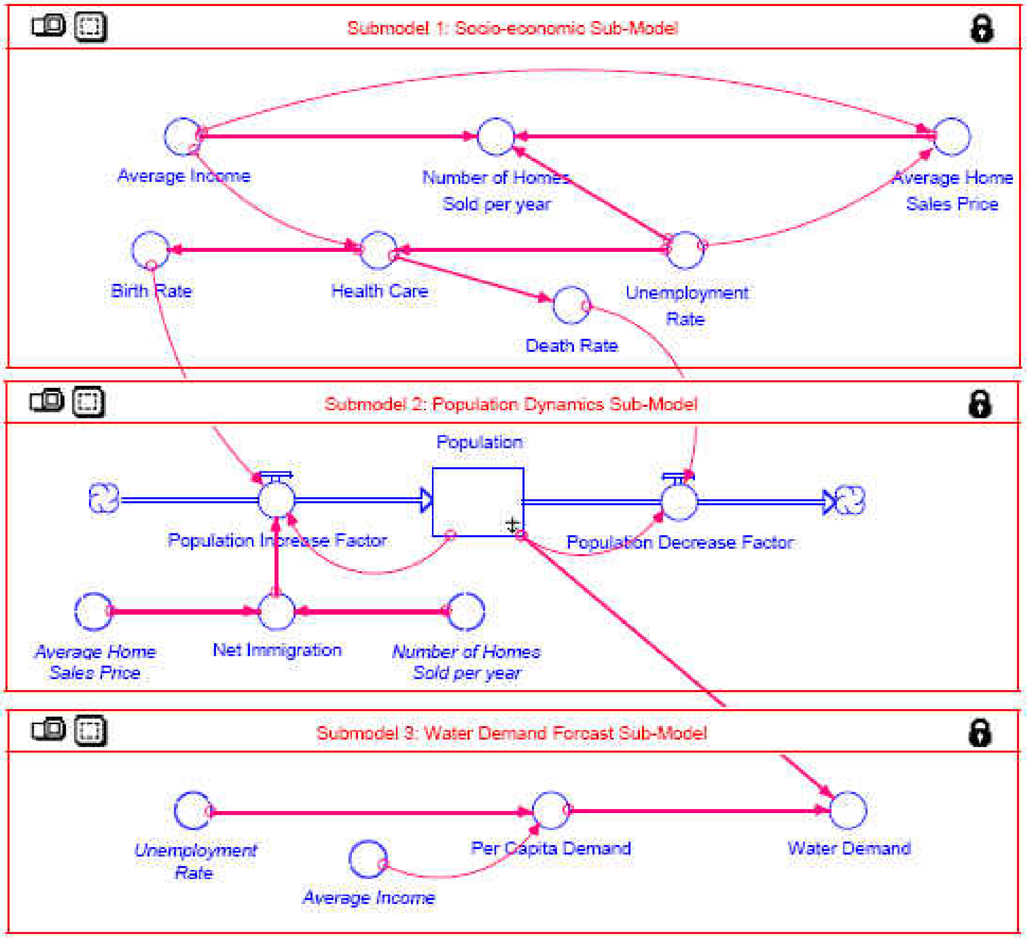


Figure 4-1 The system dynamics model for domestic water demand estimation

Table 4-1 Definition of socioeconomic and managerial factors

Social-Economic factor name	Definition
Population Increase Factor	The amount of population increased each year, in Manatee
Population Decrease Factor	The amount of population decreased each year, in Manatee
Net immigration	The amount of population increase due to net immigration, in Manatee
Birth rate	The percentage of birth among the population, in Manatee
Death rate	The percentage of death among the population, in Manatee
Population	The amount of population, in Manatee
Health care	The number of uncovered by health insurance, in Florida
Number of homes sold per year	The average number of houses sold per year, in Manatee
Average home sales price	The annual average home sales price, in Manatee
Per capita Demand	The daily average water demand per capita, in Manatee
Unemployment rate	Unemployment rate, in Florida
Average income	Average annual income, in Florida
Water demand	Domestic water demand per day, in Manatee

Observational evidences in the literature show that the intrinsic relationships between these socioeconomic and managerial factors exist either causally or statistically. The intrinsic relationships between real estate market and macroeconomic fluctuations were well documented (Case, 1991; Case et al., 2000). The involvement of real estate impact on the economic cycling has been found in New England, California, Alaska and Hawaii (Case, 1991; Case et al., 2000). It shows 72 percent of all bank lending during the boom from 1984 to 1988 was collateralized with real estate, and the real estate loans accounted for more than 90 percent of Bank of New England's losses in the economic downturn from 1988 to 1992 (Case, 1991; Case et al., 2000). Rising housing prices in the boom fueled consumer spending and expanded the employment rate. However, in the economic downturn, mortgage default rates and foreclosures rate were high, and losses were severe which, in turn, affected the real estate value and turnovers. In our model, the statistical linkages between real estate market (average home sales price and number of homes sold per year) and the macroeconomic indicators (unemployment rate and average annual income) were established using statistical regression analysis. Based on the local data collected in Florida and Manatee County from 2003 to 2009, the linkages were proved significant (see Table 4-2).

Our findings indicate that the local real estate market can be further interrelated with the immigration movement. Burnley et al. (1997) reported that immigration was one of the important short- and long-term driving forces of real estate market. Saiz (2003, 2007) provided the evidence of a causal relationship between immigration inflows and housing market in American cities. Thus, a quantitative linkage between the net immigration rate and the real estate market (e.g. average home sales price and number of homes sold per year) became available in our system dynamics model. Such a linkage was also proved significant based on the local historical data in Manatee County (see Table 4-2). By the same token, Kuttner (1999) reported that most Americans rely on their employers for health insurance. In 1997, of the 167.5 million nonelderly Americans with private health insurance, 151.7 million belonged to employer-provided health plans (Fronstin, 1998). Parkin et al. (1987) stated that it was well known that a strong relationship existed between the national expenditures on health care and the national income. Insurance premiums and income are the factors for those who are not included in the employer-sponsored health plans. Therefore, health care level (e.g. the number of uncovered) is interrelated to unemployment rate and average annual income. Local data in Manatee County and Florida shows that such a linkage is significant. Health care level can also indicate the fertility and mortality. Wennberg et al. (1987) found a statistical relationship between medical insurance claim data and health care outcomes so that the data maintained by medical insurance plans could be used to evaluate the incidence of birth and death. Hence, it is possible to link the health care and the death rate together quantitatively. The relationship between the population increase, the birth rate and the net immigration inflows are thus intimately related with each other in the end, as addressed in our system dynamics model. Finally, the water demand forecast submodel can be defined on the basis of per-capita water demand so that it is affected by both unemployment rate and average annual income. With this endeavor, impacts of changing macroeconomic environments may be allowed to propagate throughout the whole system dynamics model leading to a sound elucidation of the trend of water demand related to primary socioeconomic factors.

Table 4-2 Regression and empirical equations derived in support of the system dynamics model

Socioeconomic Factors	**Empirical Equations**		
Population Increase Factor	= Population * Birth rate + Net immigration		
Remark	Population increase factor is the sum of new births and net immigration.		
Population Decrease Factor	= Population * Death rate		
Remark	Population decrease factor is the amount of deaths.		
Water Demand	= PerCapita Demand * Population		
Remark	It is a theoretical equation for water demand that total demand equals to the product of population and per capita demand.		
	Regression Equations	R^2	p-value
Net immigration	= – 3030 + 0.783*Number of homes sold per year – 0.00000011*Average home sales price*Average home sales price	86.7%	0.002
Remark	There is causal relationship between immigration inflows and real estate market and positive correlation was found according to Saiz (2003, 2007)		
Birth rate	= 0.00813 + 0.000001 * Health care	66.0%	0.026
Remark	Birth rate is statistically related to the health insurance coverage according to Wennberg et al. (1987)		
Death rate	= 0.014 – 0.000001 * Health care	86.7%	0.002
Remark	Death rate is statistically related to the health insurance coverage according to Wennberg et al. (1987)		
Health care	=4513 – 1061*Unemployment rate + 0.0237*Average income*Unemployment rate	95.1%	0.002
Remark	Health insurance is related to the unemployment rate and income (Fronstin, 1998; Kuttner, 1999)		
Number of homes sold per year	= 30616 – 0.000046*Average income*Average income + 0.082*average home sales price + 0.018*average home sales price*unemployment rate	95.3%	0.040
Remark	Case (1991) and Case et al.(2000) show the intrinsic relationship between the real estate market and macroeconomy		
Average home sales price	= 368990 – 129770*Unemployment rate + 2.81*Unemployment rate*average income	97.3%	<0.000
Remark	Case (1991) and Case et al.(2000) show the intrinsic relationship between the real estate market and macroeconomy		
Per capita Demand	= 122 – 0.000269*Unemployment rate*average income +0.594*Unemployment rate*Unemployment rate	87.8%	0.015
Remark	Per capita demand is driven by the two macroeconomic indicators.		
Average income	= –2164909 + 1097 * Year number	97.2%	0.000
Remark	average annual income presents strong linear property over years as shown in Figure 3.		

Water price is a well-known factor that may have impacts on the per-capita water demand. However, it is not included in this model. One of the reasons is that the demand of water is of fundamentally importance in our daily life and there is no substitute of water resources anyhow. In addition, water bills are not typically a big proportion of expense in the sense that the elasticity of water demand is not a sensitive one to be considered (Savenije and van der Zaag, 2002). Therefore, domestic water demand was deemed inelastic to the water price even though the price elasticity may be slightly different from zero in our system dynamics model.

Note that the majority of the historical data that were used in our study came from the U.S. Census Bureau and U.S. Department of Labor. Statistical regression analyses associated with these internal linkages within and between submodels were then available based on the historical data from 2003 to 2009. These linkages are also supported by literature being reviewed. Thus, Table 4-2 summarizes all the derived equations and associated remarks of those relevant factors.

4.1.2 Model Validation

The proposed system dynamics model was validated by comparing the estimated values against the historical data from 2003 to 2009. The model starts its simulation runs in the year 2003 with the designated initial data for the stock component (e.g. population). Unemployment rate, as one of the macroeconomic driving forces, was replaced by the real historical recorded data. Another macroeconomic driving force, namely the average annual income, was also estimated by using the regression equation described in Table 4-2. Thus, the model-based output for Manatee County domestic water demand can be shown in Figure 4-2, which is denoted as the base model output in this study. Apparently, the model-based estimation curve is pretty close to the actual historical curve confirming the fidelity of the proposed system dynamics model. The prediction accuracy of domestic water demand estimation in Manatee County from 2003 to 2009 can be further evidenced based on the relatively higher R^2 value (i.e., 78.72%). Therefore, the development of this system dynamics model is deemed successful. This validated model indicates the pattern of domestic water demand in Manatee County that is clearly driven by the Florida unemployment rate and average annual income.

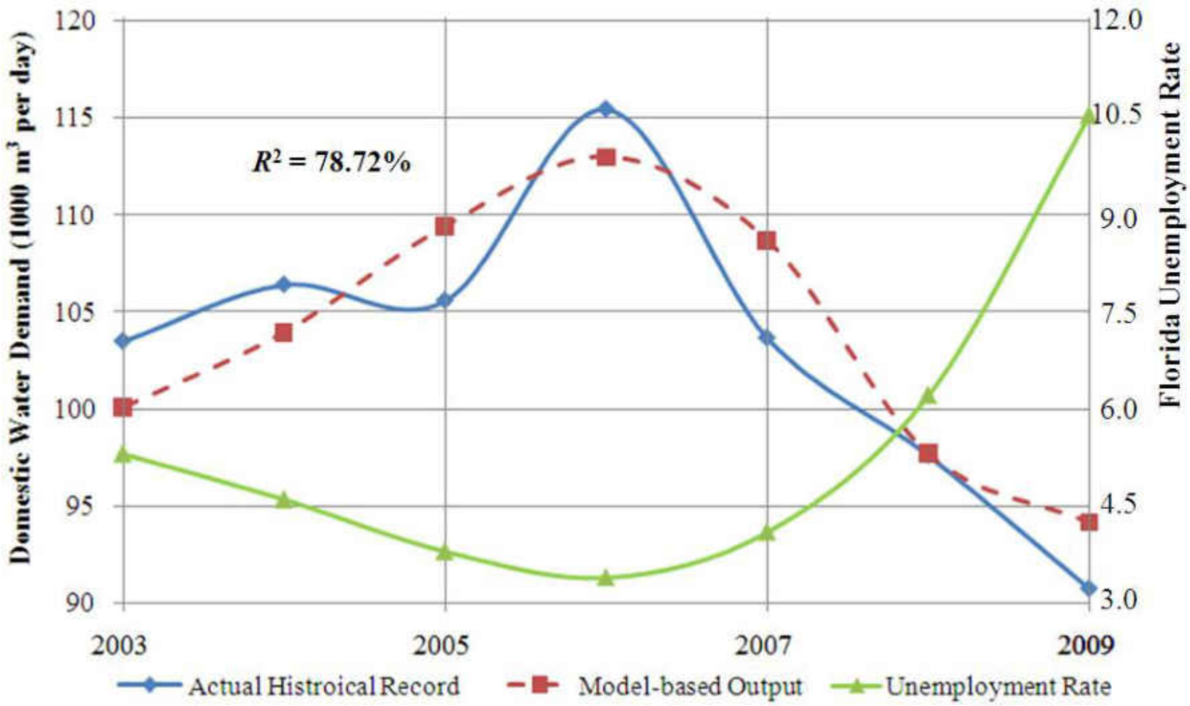


Figure 4-2 Model validation

4.2 Carbon Footprint Evaluation For A Water Infrastructure System

4.2.1 Goal And Scope Definition

The time frame of this analysis was limited from 2011 to 2030, by which the total CO_2 equivalents were estimated over the 20 years for each of the twenty alternatives, respectively. The only impact category included in this study was GWP based on the same unit of CO_2 equivalents. For the purpose of comparison, all values of carbon footprint were normalized to be based on 1 m^3 of potable water delivered, serviced and recycled in the production, use and recycle phases. With these common bases, the proposed methodology described in previous section was implemented by calculations with the aid of a software package (Gabi® 4.0 education version). Such a holistic assessment was followed by an uncertainty analysis to evaluate the reliability of the carbon footprint assessment.

Table 4-3 Description of inventory characteristics of potable water service

Characteristic	Unit	Value
Steel	1,000 t	see Section 4.2.3.1
Concrete	1,000 m^3	see Section 4.2.3.1
Diesel	L	see Section 4.2.3.1
New facilities		
piping length	km	see Section 4.2.4
reservoir size	$10^6 m^3$	see Table 4-5
WTP capacity	$10^3\ m^3 \cdot d^{-1}$	see Table 4-6

Table 4-4 The database of LCI applied in this study

Process	Unit	Power (kWh)	GHG (g)	Reference
Production of steel	kg	4.396	–	(Stubbles, 2000)
Production of cement	$10^3 m^3$	575	–	(Struble and Godfrey, 2004)
Construction of steel structure	m^2	–	400-1000	(Cole, 2000)
Construction of concrete structure	m^2	–	5000-20000	
Transportation of water by pipes	t	see Section 4.2.4.1	–	(PE International, 2009)
Raw water treatment	m^3	normal: 0.1 seawater: 0.52	–	(Friedrich, 2001; Cerci et al., 1999)
Wastewater treatment	m^3	–	409	(Pillay, 2005)
Energy from coal	kWh	1	941	(Lenzen, 2008)
Energy from gas	kWh	1	577	
Energy from oil	kWh	1	750	(Weisser, 2007)

4.2.2 Inventory And Database

All processes in the system boundary were assessed for carbon footprint calculations based on the characteristics of LCI as shown in Table 4-3. The database applied in this study is summarized in Table 4-4. Details of the carbon footprint estimation associated with construction, use, and recycle phases are given below stepwise for all alternatives.

4.2.3 Construction Phase

4.2.3.1 Raw Materials Acquisition

Raw materials acquisition analysis is the first stage of the carbon-footprint analysis in evaluating the twenty expansion alternatives. Raw materials, such as enforced steel and concrete, are used for the construction of new transmission pipes and WTP. New reservoirs are all assumed to be earthen embankments. Energy consumption for earthwork is estimated based on the data in Table 4-4. Enforced steel and concrete are the two principal raw materials in construction selected for carbon-footprint estimation. The concrete is a mixture of Portland cement with fly ash or slag, for which a modest amount of energy is required in the acquisition process. The enforced steel has higher energy consumption per unit as compared to concrete in the production phase. The energy consumed is estimated to be 2.07 $GJ \cdot m^{-3}$ or 0.89 $MJ \cdot kg^{-1}$ for concrete production (Struble and Godfrey, 2004) 15.83 $MJ \cdot kg^{-1}$ or 15 $MBtu \cdot t^{-1}$ for steel production (Stubbles, 2000). The amount of raw materials required for each of the twenty expansion alternatives is estimated using the method illustrated in Figure 4-3. In this context, we assume no enforced steel is required for the construction of new reservoirs and no concrete for new pipelines. Both concrete and enforced steel are only needed for the construction of new WTP.

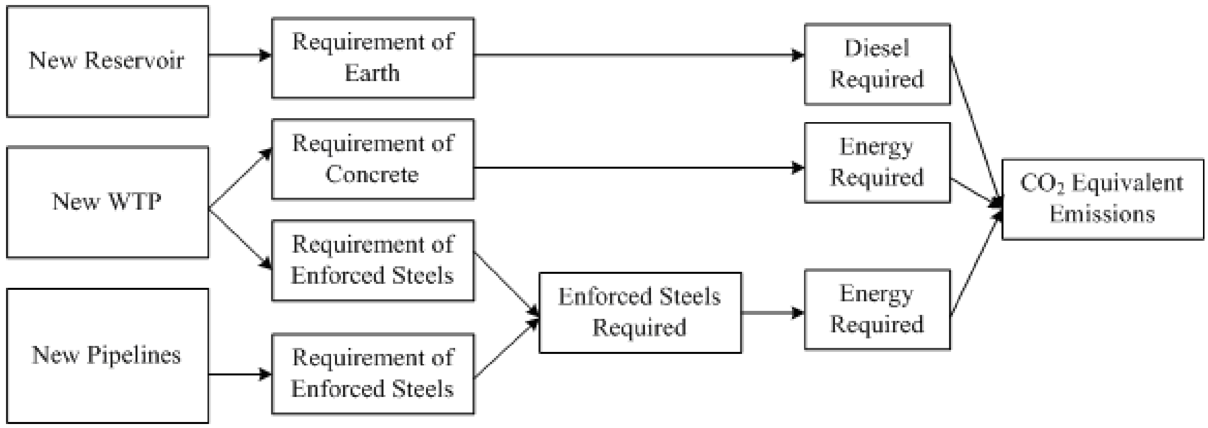


Figure 4-3 Carbon footprint estimation in construction phase

The consecutive tables (Table 4-5, Table 4-6 and Table 4-7) list all the details of earth, concrete, and steel requirements for new reservoirs, new WTPs and pipelines. The bucket of excavator grab vehicle is assumed to have a capacity of 0.96 m^3 or 1.25 yd^3 (e.g. Komatsu S4D102LE-2). Since diesel consumption for a similar size excavator grab may vary from 18 $L{\cdot}h^{-1}$ to 42 $L{\cdot}h^{-1}$ if fully loaded, an average value of 30 $L{\cdot}h^{-1}$ is assumed and selected in our calculation. We further assume that 180 buckets of earth may be excavated per hour if an excavator grab vehicle is fully loaded. Such information makes the estimation of carbon footprint associated with diesel combustion doable. According to Gabi® LCI database, carbon footprint of diesel combustion based on the CO_2 equivalent emission is 2.73 $kg{\cdot}L^{-1}$ diesel burnt. Hence, the GHG emission due to earthwork for constructing new reservoirs can be evaluated. The lengths of pipelines are approximated by measuring the horizontal distances between the Manatee County WTP and the water sources. The distances are determined by either actual piping route (e.g. regional water options) measured by Google Earth® or the suggested driving route by Google Map®. The pipe wall thickness is assumed to be 2 cm. The outer radius, *R*, is estimated based on the maximum capacity of the corresponding expansion alternative at the designed flow speed that is 1 $m{\cdot}s^{-1}$.

Table 4-5 New reservoir size and earthwork for the 20 water supply alternatives

Alternative Number	New Reservoir Size ($10^6 m^3$)	Earthwork ($10^6 m^3$)	Total number of buckets needed	Total time required (h)	Diesel needed (L)
1	0	0	0	0	0
2	0	0	0	0	0
3	0	0	0	0	0
4	0	0	0	0	0
5	0	0	0	0	0
6	7.57	0.92	960000	5333	160000
7	15.14	1.83	1920000	10667	320000
8	22.71	2.75	2880000	16000	480000
9	15.14	1.83	1920000	10667	320000
10	0	0	0	0	0
11	0	0	0	0	0
12	0	0	0	0	0
13	22.71	2.75	2880000	16000	480000
14	15.14	1.83	1920000	10667	320000
15	22.71	2.75	2880000	16000	480000
16	22.71	2.75	2880000	16000	480000
17	15.14	1.83	1920000	10667	320000
18	15.14	1.83	1920000	10667	320000
19	15.14	1.83	1920000	10667	320000
20	0	0	0	0	0

The data of new reservoir sizes are based on the information in the work plan (Manatee County Board of County Commissioner, 2008). The data point of earthwork for alternative #13 is from "Facility Expansion Fact Sheet", Peach River/Manasota Regional Water Supply Authority. All the other data points for earthwork are estimations by assuming linear proportion to the new reservoir size. Bucket size of a typical excavator grab vehicle is assumed to be 0.96 m^3 (1.25 yd^3). 180 buckets of earth are assumed to be excavated per hour if the grab vehicle is fully loaded, at which diesel consumption is assumed to be 30 $L{\cdot}h^{-1}$.

Using the proposed procedures in Figure 4-3, raw materials required for all twenty alternatives are estimated. We further assume that energy needed for the production of raw materials is generated based on the current mixed power grid (53% gas, 24% oil, and 23% coal) in 2010. According to the survey (Lenzen, 2008), the GHG intensity for black coal and natural gas are 941 $g{\cdot}kWh^{-1}$ and 577 $g{\cdot}kWh^{-1}$, respectively. The GHG intensity for oil is 750 $g{\cdot}kWh^{-1}$ (Weisser, 2007). Thus, the GHG intensity of such a mixed power grid (e.g., 53% gas, 24% oil, and 23% coal) is about 702 g•kWh^{-1}. With this information, the final CO_2 equivalent emissions estimated for the twenty alternatives can be described in subsequent subsections.

Table 4-6 New WTP capacity and raw materials for the 20 water supply alternatives

Alternative Number	New WTP Capacity ($10^3 m^3 d^{-1}$)	Concrete Needed ($10^3 yd^3$ / $10^3 m^3$)	Steel Needed ($10^3 t$)
1	0	0 / 0	0
2	0	0 / 0	0
3	0	0 / 0	0
4	0	0 / 0	0
5	0	0 / 0	0
6	0	0 / 0	0
7	0	0 / 0	0
8	0	0 / 0	0
9	0	0 / 0	0
10	0	0 / 0	0
11	0	0 / 0	0
12	0	0 / 0	0
13	181.70	12 / 9.174	1.500
14	75.71	5 / 3.822	0.625
15	75.71	5 / 3.822	0.625
16	75.71	5 / 3.822	0.625
17	56.78	3.75 / 2.866	0.469
18	53.00	3.5 / 2.676	0.438
19	53.00	3.5 / 2.676	0.438
20	37.85	2.5 / 1.912	0.313

The data of new WTP capacities are based on the information in the work plan (Manatee County Board of County Commissioner, 2008). The data point of concrete and steel need for alternative #13 is from “Facility Expansion Fact Sheet”, Peach River Manasota Regional Water Supply Authority. All the other data of concrete and steel needed are estimations by assuming that raw materials needed are linearly proportional to the new WTP capacity.

Table 4-7 The details in estimation of steel required for piping

Alternative Number	Max Water Credit ($10^3 m^3 d^{-1}$)	Max Water Credit ($m^3 s^{-1}$)	Radius of pipelines, *R*, (m)	Steel needed (m^3)	Steel needed (10^3 t)
1	8.21	0.10	0.20	541.07	4.25
2	11.36	0.13	0.22	785.54	6.17
3	7.57	0.09	0.19	572.79	4.50
4	18.93	0.22	0.28	1133.01	8.89
5	15.52	0.18	0.26	938.01	7.36
6	44.29	0.51	0.42	negligible	negligible
7	34.83	0.40	0.38	734.43	5.77
8	40.13	0.46	0.40	2453.72	19.26
9	17.79	0.21	0.28	1276.27	10.02
10	17.03	0.20	negligible	negligible	negligible
11	0	0	negligible	negligible	negligible
12	0	0	negligible	negligible	negligible
13	45.42	0.53	0.43	4807.48	37.74
14	75.71	0.88	0.55	7415.89	58.21
15	75.71	0.88	0.55	2857.30	22.43
16	75.71	0.88	0.55	2857.30	22.43
17	56.78	0.66	0.48	1748.63	13.73
18	30.28	0.35	0.35	1287.10	10.10
19	43.15	0. 50	0.42	1529.26	12.00
20	37.85	0.44	0.39	1690.46	13.27

R is the outer radius of the pipeline. Pipeline wall thickness is assumed to be 2 cm. Water flow speed is assumed to be 1 $m \cdot s^{-1}$.

4.2.3.2 Facility Construction

Limited information is available in this regard for the estimation of energy consumption needed in facility construction. To fill in the gap, it is inevitable to count on our best judgment along the track to produce the burden of carbon footprint due to facility construction. Research on carbon footprint associated with construction of reservoirs/dams and WTP facilities is still lacking since no study up to the present includes all steps required for the estimation of GHG emissions. Besides, this type of estimation of GHG emissions may vary from case to case with differing factors such as materials used, size of reservoirs, and capacity of WTP. A study

(Peisajovich et al., 1996) was conducted in Quebec, Canada indicated that the GHG emissions associated reservoir construction could be close to each other as long as the construction materials were limited to be either concrete or earth/rock. Thus, to ease the estimation of GHG emission, earthen reservoirs is chosen as basis in our assessment. According to recent assessments by Cole (Cole, 2000; Cole, 1998), steel assemblies typically emit 0.4-1.0 $kg\cdot m^{-2}$ CO_2 equivalent and concrete-based structural systems may lead to 5-20 $kg\cdot m^{-2}$ CO_2 equivalent emissions. The upper bound of values is taken for our estimation. Based on the raw materials (e.g. concrete and steel) required, we are able to estimate the approximate CO_2 equivalent emissions during the construction phase based on the estimated area of land needed for facility constructions. This is carried out based on the fact that that each square meter of the construction site requires 0.1 m^3 concrete or 0.1 t steel on average for new WTPs and 1 m^3 of earth for new reservoirs.

4.2.4 Production Phase

4.2.4.1 Raw Water Transportation

In this stage, the equivalent CO_2 emissions are generated based on shipping the raw water from raw water site to WTP in the Manatee County. According to the database of GaBi® LCA software package (PE International, 2009), the energy consumption of pipeline transportation can be estimated by Equation 4-1, where *EC* is energy consumption in unit of kilowatt-hour per cubic meter of water ($kWh\cdot m^{-3}$) distributed through piping, *U* represents the utilization rate of piping facilities in %, and *D* is denoted for the length of pipelines in kilometers. The utilization rate of pipelines is defined as the amount of actual water transported divided by the maximum transportation capacity of the pipelines.

$$EC = \frac{7.1347 \times 2.71828^{2.3413U} \times D}{1000} \tag{4-1}$$

To calculate the energy consumption per cubic meter of water each day, we estimate *D* as the horizontal distance between the raw water site and the Manatee County WTP for all the expansion alternatives except alternatives #5 and #9. Same as described in Section 4.2.3.1, *D* is determined by either actual piping route (e.g. regional water options) measured by Google Earth® or the suggested driving route by Google Map®. Although raw water may be treated at a new WTP in some alternatives, the treated water from those alternatives is assumed to be rerouted to the Manatee County WTP for distribution to customers using the current existing pipeline network, and thus the energy consumption does not change much from each other between different alternatives. Even though an increased impact may be expected relative to the current situation due to increased water supplies, such an increase can be ignored numerically when comparing all expansion alternatives together. Water supply expansion alternatives #5 and #9 are different with the rest of alternatives because of no required treatment for the surface water as the supply source is simply prepared for irrigation. As a consequence, the pipeline distances from the raw water site to the irrigation site are used as the basis for the estimation of carbon footprint in alternatives #5 and #9.

In Equation 4-1, *U* is assumed to be 100% for all twenty alternatives in which the newly constructed pipelines are required. In other words, the maximum capacity of newly built pipelines is assumed to be operated under maximum water credit that can be obtained from each water supply alternative. This assumption meets the cost-effectiveness requirement.

4.2.4.2 Treatment Of Raw Water At WTP

Energy consumption in the raw water treatment phase has no difference between alternatives from #1 to #12 in which treatment is supposed to be performed at the Manatee County WTP. For those alternatives from #13 to #19, new WTPs will be built using similar treatment processes as the same as the current Manatee County WTP. Thus, we assume the same energy consumption in the raw water treatment phase when compared with those of alternatives from #1 to #12. A study with a similar WTP treatment process in eThekwini Municipality (South Africa) was conducted and energy consumption was reported as 0.10 kilowatt-hour per cubic meter treated water (Friedrich, 2001). That is equal to 70.2 g CO_2 equivalents in terms of GWP assuming that the energy comes from the same mixed power grid (e.g., 53% gas, 24% oil, and 23% coal).

Energy consumption is significantly higher for the seawater desalination used as a unit process in alternative #20. A study of desalination process (Cerci et al., 1999) indicated that the energy consumption depends on the salinity level of source seawater and recovery ratio of membrane treatment. At the assumed 35 $g \cdot L^{-1}$ salinity for seawater in the Tampa Bay area, the minimum energy required was 0.52 kilowatt-hour per cubic meter water treated at a recovery rate 40% (Cerci et al., 1999). This rate corresponds to 365.04 g CO_2 equivalents of GWP when the energy comes from the same mixed power grid (53% gas, 24% oil, and 23% coal). Up to this point, we are able to summarize the energy consumption and corresponding CO_2 equivalent emissions in the raw water treatment phase for all the twenty alternatives (Table 4-8)

Table 4-8 Carbon footprint in raw water treatment phase

Alternative Number	Energy consumption Unit: $kWh \cdot m^{-3}$	CO_2 equivalent emissions Unit: $g \cdot m^{-3}$
1 ~ 19	0.10	70
20	0.52	365

4.2.5 Use Phase

4.2.5.1 Potable Water Distribution

Energy consumption for potable water distribution is the same for all the twenty alternatives that use the same existing piping networks for distribution. The drinking water distribution pipes in the Manatee County system have a total length of 2,234.19 km (1,388.56 miles) with a maximum capacity of 317,975 $m^3 \cdot d^{-1}$ (84 million gallons per day). Based on the water demand projection in the work plant, the total demand at wholesale quantity will reach 234,431 $m^3 \cdot d^{-1}$ (61.93 million gallons per day) by year 2030. Thus, in the year 2030, the treated potable water pipeline utilization rate, U, will be 234,431÷317,975 = 73.73%.

We estimated energy requirements for the potable water distribution phase by using Equation 4-1. An accurate estimation can be obtained from hydraulic modeling of water distribution in a future network configuration, including pump scheduling and pressure zone management (Walski et al., 2009). The uncertainty in future network configuration and management makes this type of calculation unattainable. Instead, using Equation 4-1 is a feasible way for the purpose of alternative screening only. For the topographically flat service area of the district, the energy consumption can be estimated for a median piping distance from the WTP. In Figure 4-4, the boundaries of the Manatee County are represented by solid lines. Its service area is measured using tools in Google Earth®. Sarasota County, as a wholesale customer, is right next to Manatee County in the south. Assuming that residents are uniformly distributed in Manatee County and Sarasota County, the median distance (R_{median}) between the Manatee County WTP and customers is given in Equation 4-2.

$$\pi R_{\text{median}}^2 = 59.5 \text{ km } \times 48 \text{ km} \tag{4-2}$$

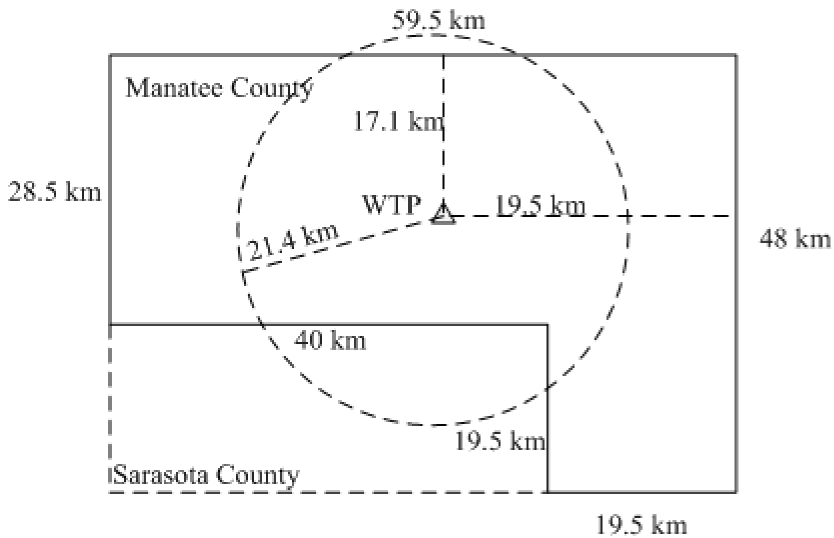


Figure 4-4 Location of WTP and median distance to customers

Based on these simplifications, the median distance between Manatee County and customers is 21.4 km. The energy consumption in the potable water distribution phase, calculated from Equation 4-1, is 0.858 kWh·m^{-3}. This equals 602.32g equivalents of CO_2 emission when the energy comes from the same mixed power grid (e.g., 53% gas, 24% oil, and 23% coal).

4.2.5.2 <u>Sewage And Wastewater Collection</u>

Energy consumption in sewage and wastewater collection is indifferent among the twenty water supply expansion alternatives. According to the work plan, three wastewater treatment plants (WWTP) are in operation providing wastewater service for Manatee County (Figure 4-5). Similarly by assuming uniform distribution of residents in Manatee County and Sarasota County, we estimate the median distance of 12.35km between the WWTPs and customers. We further assume that the sewage and wastewater collection rate is 80% of potable water serviced, and estimated the rate of 187,544.8 $m^3 \cdot d^{-1}$ in wastewater collection by 2030. Assuming that the capacity of pipeline for wastewater collection is the same as that for potable water delivery, the utilization rate of wastewater collection pipelines is 58.98%. We recognized that energy consumption in wastewater collection varies significantly between locations. For most wastewater utilities, wastewater collection is composed of gravity drains and booster pump stations. Due to the flat topography of the Manatee County, we assumed most wastewater streams were shipped by pumping in our analysis. Let U = 58.98% and D = 12.35 km. By applying Equation 4-1, we obtain an energy consumption of 0.351 $kWh \cdot m^{-3}$. The equivalent CO_2 emission is 246.40 g when the energy comes from the same mixed power grid (e.g., 53% gas, 24% oil, and 23% coal).

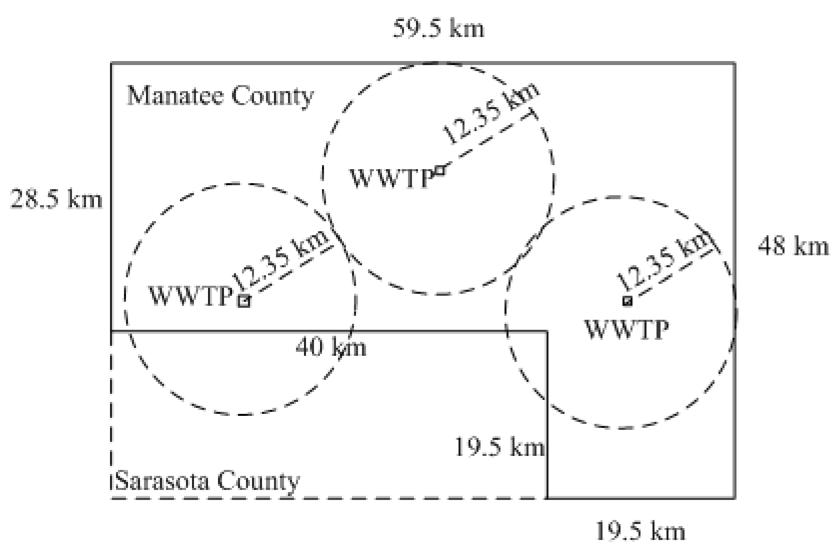


Figure 4-5 Locations of WWTPs and median distance to customers

4.2.6 Recycle Phase

4.2.6.1 Treatment Of Wastewater At WWTPs

All the three WWTPs in Manatee County have applied the same secondary wastewater treatment process. Thus, there is no difference in energy consumption if wastewater is treated in one of the three WWPs. In a similar carbon footprint analysis study conducted for wastewater treatment in eThekwini Municipality, South Africa, it shows that 112g CO_2 equivalent emissions for primary treatment and 297 g CO_2 equivalent emissions for secondary treatment per cubic meter wastewater can be quantified (Pillay, 2005), For the case when wastewater generation rate is 80%,, the phase of wastewater treatment will generate about 238g CO_2 equivalent emission per cubic meter drinking water consumed in the district.

4.2.6.2 Reclaimed Water Reuse Or Discharge To Rivers

In this stage of the potable water service, reclaimed water from wastewater treatment plant is either discharged to rivers or to irrigation fields. Since rivers and irrigation fields are not potable water users, they may have different topographies between these two locations. Thus, we assume that reclaimed water is transported to irrigation fields or rivers by gravity from which no energy consumption and no GHG emissions will occur.

4.3 Multiobjective Programming For Water System Optimization

In the quantitative analysis, the multistage planning horizon was divided into four time periods with each having a 5-year time span. Decisions in each period as to how many new water supply alternatives need to be picked up to meet the growing water demand can be assessed via a trade-off between the two objectives subject to associated constraints. Together with a set of technical, managerial, and social constraints, the model is able to output a set of decision variables for calculation of the amount of water that may be generated from a selected water supply alternative in a specific time period and its associated environmental impact in terms of CO_2 equivalent emissions.

4.3.1 Multiobjective And Multistage Mixed Integer Programming Model

4.3.1.1 Objective Functions

The following formulation of two objective functions implements the prescribed technical setting of 5-year operation per time period. All monetary values associated with cost terms are discounted value to the year 2007. These two objectives are deemed comparable with each other in decision making which implies that there is no hierarchical relationship in between.

Objective function 1: Minimize Z_1 = total CO_2 equivalent emissions, unit: g

$$= \sum_{i=1}^{20} (1000 A_{i1} \mathrm{CO2eo}_i \times 365 \times 5 + Y_{i1}\,\mathrm{CO2ec}_i) + \sum_{t=2}^{4} \sum_{i=1}^{20} [1000 A_{it} \mathrm{CO2eo}_i \times 365 \times 5 + (Y_{it} - Y_{i(t-1)})\,\mathrm{CO2ec}_i]$$

Objective function 2: Minimize Z_2 = total cost, unit: \$

$$= \sum_{i=1}^{20} (1000 A_{i1} C_i \times 365 \times 5 + Y_{i1} F_i) + \sum_{t=2}^{4} \sum_{i=1}^{20} [1000 A_{it} C_i \times 365 \times 5 + (Y_{it} - Y_{i(t-1)}) F_i]$$

in which Y_{it} is 1 if alternative i is implemented in and after time stage t; otherwise $Y_{it} = 0$, $i = 1, 2, \ldots, 20$; $t = 1, 2, 3, 4$. $\mathrm{CO2ec}_i$ is the amount of CO_2 equivalent emissions in the construction phase of alternative i in unit of g, and $\mathrm{CO2eo}_i$ is the amount of CO_2 equivalent emissions in the operational phase of alternative i in unit of $g \cdot m^{-3}$, $i = 1, 2, \ldots, 20$. A_{it} is actual water withdraw ($10^3 m^3 d^{-1}$) from alternative i, $i = 1, 2, \ldots, 20$, $t = 1, 2, 3, 4$. C_i is unit water cost of solution i in $\$ \cdot m^{-3}$, $i = 1, 2, \ldots, 20$. F_i is Fixed capital investment for alternative solution i, $i = 1, 2, \ldots, 20$.

4.3.1.2 Constraints

Constraint set in this compromise programming model includes definitional constraints, water demand constraints, capacity limitation constraints, availability constraints, sequencing constraints, mutually exclusive constraints, irreversible constraints, and screening constraints, and non-negative and binary constraints. These constraints provide different functionalities in an intertwined solution space that uniquely narrow down the dynamic selection and ranking based on the streamlined logic as described by the coupled objective functions and constraints over the planning horizon.

a) Definitional constraints: This set of constraints defines the current maximum water supply and projected water demand in each time period in thousand cubic meters per day. All of them empower the final decision analysis collectively to bridge the objectives and constraint set.

$$S = 200.04 \quad 10^3 m^3 d^{-1} \qquad (4\text{-}3)$$

$$D_1 = 192.19 \quad 10^3 m^3 d^{-1} \qquad (4\text{-}4)$$

$$D_2 = 209.14 \quad 10^3 m^3 d^{-1} \qquad (4\text{-}5)$$

$$D_3 = 211.83 \quad 10^3 m^3 d^{-1} \qquad (4\text{-}6)$$

$$D_4 = 234.43 \quad 10^3 m^3 d^{-1} \qquad (4\text{-}7)$$

$$F_i = 0.001 \quad \$ \qquad (4\text{-}8)$$

$$G = \text{an ultra big number (e.g., 999999999)} \qquad (4\text{-}9)$$

in which S is current water supply upper bound. D_t is water demand in time period t (= 1, 2, 3, 4). G is a dumb number in programming for computing stability to support the simultaneous screening based on the If-Then logic in Constraints (4-24)~(4-26). F_i is the virtual fixed cost that is artificially assigned small number relative to all cost parameters to aid in screening logic in cost-effectiveness objective and associated constraints. The settings of F_i and G can also help avoid a void selection of an alternative with no actual water supply over the planning horizon.

b) Water demand constraints: This set of constraints between demand (D) and supply (S) apply to the entire 20-year period in modeling space:

$$\sum_{i=1}^{20} A_{it} \geq D_t - S \qquad \text{for all } t \tag{4-10}$$

c) Capacity limitation constraints: This set of constraints assures that the water amount supplied by each future water source will not exceed its predetermined supply limit.

$$A_{it} \leq A_i^{\max} Y_{it} \qquad \text{for all } t \text{ and all } i \tag{4-11}$$

in which $A_i^{\max}$ is the maximum water credit ($10^3 m^3 d^{-1}$) for A_i, $i = 1, 2, \ldots, 20$.

d) Availability constraints: This set of constraints assures that only MARS-I and MARS-II can be available in time period 1 and the rest of future water supply alternatives may be available only after time period 1 because of the original setting in the work plan.

$$Y_{i1} = \begin{cases} 1 & i = 1, 2 \\ 0 & i = 3, 4, \ldots, 20 \end{cases} \tag{4-12}$$

e) Sequencing constraints: This set of constraints assures that MARS-II project is not able to be implemented until implementation of MARS-I project because of the original setting in the work plan. Similarly, MARS-II project must be implemented ahead of the implementation of MARS-III project. This forward-looking sequence is also applied for MARS-III project which must be implemented ahead of MARS-IV project.

$$\begin{aligned} Y_{1t} &\geq Y_{2t} \\ Y_{2t} &\geq Y_{3t} \qquad \text{for all } t \\ Y_{3t} &\geq Y_{4t} \end{aligned} \tag{4-13}$$

f) <u>Mutually exclusive constraints</u>: Some of the future water supply alternatives are mutually exclusive based on the original setting in the work plan. This set of constraints assures that only one of exclusive future water supply alternatives may be implemented in any time period. For example, alternatives 11 and 12 are mutual exclusive since water use permit is either transferred to developers or purchased by Manatee County. MARS-III project has conflicts with regional water supply alternatives because any one of the regional water supply sources or completed implementation of MARS projects will provide enough water supply capacity according to the work plan (Board of County Commissioner, 2008). Alternatives 15 and 16 are mutually exclusive because both alternatives use the same water supply sources with different implementation schedules. Similarly, alternatives 17, 18 and 19 are mutually exclusive because all of the three alternatives count on Flatford Swamp as a water source. The differences among the three are linked with whether we have to build a new WTP and whether this site will be implemented as a regional water supply option. Alternatives 9, 18 and 19 are mutually exclusive because all of the three are tied with a new reservoir site at Tatum. The difference is whether the new reservoir site will be used to store water pumped from Myakka River or from Flatford Swamp. Constraints (4-19)~(4-22) illustrate the need of having MARS I in place at first before allowing the other relevant alternative 5, 9, 10, and 11 to be selected because of the sequential credit transfer.

$$Y_{11t} + Y_{12t} \le 1 \qquad \text{for all } t \qquad (4\text{-}14)$$

$$Y_{3t} + Y_{13t} + Y_{14t} + Y_{15t} + Y_{16t} + Y_{17t} \le 1 \qquad \text{for all } t \qquad (4\text{-}15)$$

$$Y_{15t} + Y_{16t} \le 1 \qquad \text{for all } t \qquad (4\text{-}16)$$

$$Y_{17t} + Y_{18t} + Y_{19t} \le 1 \qquad \text{for all } t \qquad (4\text{-}17)$$

$$Y_{9t} + Y_{18t} + Y_{19t} \le 1 \qquad \text{for all } t \qquad (4\text{-}18)$$

$$Y_{5t} \le Y_{1t} \qquad \text{for all } t \qquad (4\text{-}19)$$

$$Y_{9t} \le Y_{1t} \qquad \text{for all } t \qquad (4\text{-}20)$$

$$Y_{10t} \le Y_{1t} \qquad \text{for all } t \qquad (4\text{-}21)$$

$$Y_{11t} \le Y_{1t} \qquad \text{for all } t \qquad (4\text{-}22)$$

g) Irreversible constraints: This set of constraints assures that the implemented water supply alternatives in one time period will be available in and after that time period.

$$Y_{it} \le Y_{i(t+1)} \qquad i = 1, 2, \ldots, 20,\ t = 1, 2, 3 \qquad (4\text{-}23)$$

h) Screening constraints: The set of constraints assures that the inclusion of a new water supply alternative at a time in the screening process is considered when the maximum capacity of current water supply in the current time period is not able to meet the projected water demand in the next time period. Otherwise, there is no need to implement any water supply alternative as long as there are enough water supplies. In Constraints (4-24)~(4-26), the formulation would allow n number of water supply alternatives to be included in each time period for capacity expansion, in which n is a positive integer. If n =1, it implies the model would only pick up one alternative at a time for ranking in sequence. Three different scenarios were analyzed, which include n =1, n =2 and n =3, respectively, in our case study, to address the number of alternatives that are allowed to be selected at a time.

$$\begin{aligned} &\sum_{i=1}^{20} Y_{i1} A_i^{\max} - (D_2 - S) < GY_1 \\ &\sum_{i=1}^{20} Y_{i2} - \sum_{i=1}^{20} Y_{i1} \le n(1 - Y_1) \end{aligned} \qquad (4\text{-}24)$$

$$\begin{aligned} &\sum_{i=1}^{20} Y_{i2} A_i^{\max} - (D_3 - S) < GY_2 \\ &\sum_{i=1}^{20} Y_{i3} - \sum_{i=1}^{20} Y_{i2} \le n(1 - Y_2) \end{aligned} \qquad (4\text{-}25)$$

$$\sum_{i=1}^{20} Y_{i3} A_i^{\max} - (D_4 - S) < GY_3$$
$$\sum_{i=1}^{20} Y_{i4} - \sum_{i=1}^{20} Y_{i3} \le n(1 - Y_3) \qquad (4\text{-}26)$$

in which Y_1, Y_2, and Y_3 are binary integer variable for screening of multiple alternatives associated with differing scenarios in the optimization context.

i) Non-negative and binary constraints: This set of constraints assures that the amount of water assigned to each water supply alternative is non-negative and the binary decision variables are dichotomous.

$$A_{it} \ge 0 \qquad (4\text{-}27)$$

$$Y_{it} = 0,1 \qquad i = 1, 2, \ldots, 20,\ t = 1, 2, 3, 4 \qquad (4\text{-}28)$$

$$Y_1, Y_2, Y_3 = 0, 1 \qquad (4\text{-}29)$$

4.3.2 Solution Procedure

4.3.2.1 Solution Space And The Pareto Optima Solutions

We can obtain the ideal solution of the multi-objective model defined in Section 4.3.1 by solving each of the individual objectives sequentially. The ideal solution (shown in Table 4-9) is considered optimal when each objective is optimized individually and achieved at the same time. However, the ideal solution may not be feasible given that the objectives may be competing, even conflicting in the decision space for which the “Pareto Optima” solution set is commonly used. The solution optimization is then transferred to finding the Pareto Optima frontier in the solution space of a compromise programming model. Alternatively, the compromised solution can be also obtained by applying the distance-based metrics defined in solving the compromise programming model (Zeleny, 1973).

Table 4-9 Ideal solution of the multi-objective model

	Minimize Z_1 (g)	Minimize Z_2 ($)
$n = 1$	1.22×10^{12}	2.23×10^{8}
$n = 2$	7.53×10^{11}	1.72×10^{8}
$n = 3$	7.29×10^{11}	1.72×10^{8}

4.3.2.2 Solution Space And Pareto Optimal Solutions

Since there are two objective functions in the model, the solution space is a two dimensional objective space with the *x*-axis defined for CO_2 equivalent emissions (Z_1) and the *y*-axis for total system cost (Z_2). The possible numerical range of Z_1 can be found by solving two single objective optimization models with an objective function to minimize Z_1 and maximize Z_1, respectively, subject to Constraints (4-3)~(4-29). The same method is also applicable for the range of Z_2. We denote that the lower and upper bounds of Z_1 as $Z_1^{\min}$ and $Z_1^{\max}$. Similarly, $Z_2^{\min}$ and $Z_2^{\max}$ are the lower and upper bounds of Z_2. For every feasible point of Z_1^{p} and Z_2^{p}, they must fall in the range between $Z_1^{\min}$ and $Z_1^{\max}$ or $Z_2^{\min}$ and $Z_2^{\max}$. Hence, we have $Z_1 = Z_1^{\mathrm{p}}$ and $Z_2 = Z_2^{\mathrm{p}}$. This leads to the generation of the solution set $\left\{(Z_1^{\mathrm{p}}, Z_2^{\mathrm{p}}) \middle| \text{all p}\right\}$ consisting of all the Pareto optimal points. However, in case of unlimited number of Z_1^{p} and Z_2^{p} in the range bounded by the upper and lower limit and *p* indicates any possible solution in between, we have to discretize the feasible solution range along the Z_1 and Z_2 dimension by dividing them into several small intervals. For example, we denote *ind* as the indifferent amount of CO_2 equivalent emissions that decision makers may feel indifferent with each other. Thus, the feasible range of Z_1 may be discretized to $(Z_1^{\min}, Z_1^{\min} + ind)$, $(Z_1^{\min} + ind, Z_1^{\min} + 2ind)$, …, $(Z_1^{\min} + l \times ind, Z_1^{\max})$ where $l = f\left[(Z_1^{\max} - Z_1^{\min}) / ind\right]$, and *f* is a flooring function that returns the maximum integer that is less than $(Z_1^{\max} - Z_1^{\min}) / ind$, which must be defined inherently. Similarly, for the interval of $(Z_1^{\min} + m \times ind, Z_1^{\min} + (m+1) \times ind)$, we may solve a single objective optimization model with the objective function to minimize Z_2 subject to those constraints defined by Constraints (4-3)~(4-32).

$$Z_1 \geq Z_1^{\min} + m \times ind \qquad (4\text{-}30)$$

$$Z_1 \leq Z_1^{\min} + (m+1) \times ind \qquad (4\text{-}31)$$

$$Z_2 \leq Z_2^{m-1} \qquad (4\text{-}32)$$

$m = 0, 1, \ldots, l$, Z_1^m and Z_2^m are the corresponding optimal solutions, and $Z_2^{-1} = \infty$.

4.4 Application Of Nested Minimax Regret Solution Method

As presented in Section 3.4, the complexity of the nested minimax regret solution method increases exponentially with the increase of the scale of the original multiobjective interval linear program and the number of uncertainties in the objective functions. The number of constraints in the minimax regret solution is $[p(2^n + 1) + m]$ excluding the non-negativity constraints where n is the number of uncertainties in the objective functions, p is the number of objectives (p = 2) in our study area, and m is the number of constraints. Due to such limitation, we apply the nested minimax regret solution method to a reduced scale version of our study area in Manatee County, Florida. In the reduced scale version of study area, we combine water supply alternatives in the same category into one option. Thus, there are five potential water supply options available for Manatee County, which are ground water options, surface water options, regional water options, transferred water options and other options. Whereas the combined uncertain maximum water credits and unit costs for the five water supply options can be seen in Table 4-10, the combined uncertain CO_2 equivalent emissions in construction phase and operational phase for the five water supply options can be found out in Table 4-11. In addition, we only consider facility expansion strategy under uncertainties for the entire 20-year-planning-period in the reduce scale version of study area, rather than a multiple time stage analysis.

Table 4-10 Uncertain maximum water credit and unit cost for each water supply option

	Water Supply Categories	Max Water Credit	Unit Cost
I	Ground Water Options	[7.57, 18.93]	[0.31, 0.53]
II	Surface Water Options	[15.52, 44.29]	[0.51, 1.09]
III	Transferred Water Options	17.03	0.5
IV	Regional Water Options	[45.42, 75.71]	[0.30, 0.76]
V	Other Options	[30.28, 43.15]	[0.55, 1.07]

Max Water Credit: 1,000 m^3d^{-1} Unit Cost: \$ m^{-3}

Table 4-11 Uncertain GHG emissions for each water supply option

	Water Supply Categories	CO_2 equivalent emissions in construction phase (g)	CO_2 equivalent emissions in operational phase ($g \cdot m^{-3}$)
I	Ground Water Options	[1.31×10^{10}, 2.75×10^{10}]	[2346, 2865]
II	Surface Water Options	[1.88×10^{10}, 1.16×10^{11}]	[1156, 3745]
III	Transferred Water Options	0	1156
IV	Regional Water Options	[8.31×10^{10}, 2.22×10^{11}]	[2706, 6853]
V	Other Options	[4.31×10^{10}, 7.76×10^{10}]	[2706, 3278]

4.4.1 Multiobjective Interval Linear Programming Model Formulation

We define GY_i is 1 if water supply category i is implemented; otherwise $GY_i = 0$, $i = 1, 2, \ldots, 5$. $GHGc_i^{\pm}$ is the uncertain amount of CO_2 equivalent emissions in the construction phase of water supply category i in unit of g, and $GHGo_i^{\pm}$ is the uncertain amount of CO_2 equivalent emissions in the operational phase of water supply category i in unit of $g \cdot m^{-3}$, $i = 1, 2, \ldots, 5$. GA_i is actual water withdraw ($10^3 m^3 d^{-1}$) from alternative i, $i = 1, 2, \ldots, 5$. $GC_i^{\pm}$ is the uncertain unit water cost of water supply category i in $\$ \cdot m^{-3}$, $i = 1, 2, \ldots, 5$. F_i is Fixed capital investment for alternative solution i, $i = 1, 2, \ldots, 5$. Thus, we have the two objective functions with uncertain coefficients as defined below.

Objective function 1: Minimize Z_1 = total CO_2 equivalent emissions, unit: g

$$= \sum_{i=1}^{5} (1000 GA_i \times GHGo_i^{\pm} \times 365 \times 20 + GY_i \times GHGc_i^{\pm})$$

Objective function 2: Minimize Z_2 = total cost, unit: $

$$= \sum_{i=1}^{5} (1000 GA_i \times GC_i^{\pm} \times 365 \times 20 + GY_i \times F_i)$$

As water supply alternatives are combined to only five categories, there will be a reduced constraint set as well because some constraints (such as sequencing constraints, mutual exclusive constraints and etc.) are no longer applicable. The constraint set is summarized as below.

a) Definitional constraints:

$$S = 200.04 \quad 10^3 \mathrm{m}^3 \mathrm{d}^{-1} \tag{4-33}$$

$$GD^{\pm} = 234.43 \pm 10\% \quad 10^3 \mathrm{m}^3 \mathrm{d}^{-1} \tag{4-34}$$

$$F_i = 0.001 \quad \$ \tag{4-35}$$

in which S is current water supply upper bound. $GD^{\pm}$ is the uncertain water demand in planning time period. We arbitrarily impose 10% random error into the projected water demand. F_i is the virtual fixed cost that is artificially assigned small number relative to all cost parameters to aid in screening logic in cost-effectiveness objective and associated constraints.

b) Water demand constraints:

$$\sum_{i=1}^{5} GA_i \geq GD^{\pm} - S \tag{4-36}$$

c) Capacity limitation constraints:

$$GA_i \leq GA\max_i^{\pm} GY_i \qquad \text{for all } i \tag{4-37}$$

in which $GA\max_i^{\pm}$ is the uncertain maximum water credit ($10^3\mathrm{m}^3\mathrm{d}^{-1}$) for GA_i.

d) Non-negative and binary constraints:

$$GA_i \geq 0 \qquad i = 1, 2, \ldots, 5 \tag{4-38}$$

$$GY_i = 0,1 \qquad i = 1, 2, \ldots, 5 \qquad (4\text{-}39)$$

4.4.2 Application Of The NMMR Method

We follow the NMMR solution method step by step as proposed in Section 3.4.2. We define $\Omega_{\boldsymbol{\alpha}}$ as the feasible solution region at the degrees of satisfaction matrix $\boldsymbol{\alpha}$ such that $\Omega_{\boldsymbol{\alpha}} = \{\mathbf{X} \mid \mathbf{A}^{+}\mathbf{X} - (\mathbf{E} - \boldsymbol{\alpha})(\mathbf{A}^{+}\mathbf{X} - \mathbf{A}^{-}\mathbf{X}) \le \mathbf{B}^{+} - \boldsymbol{\alpha}(\mathbf{B}^{+} - \mathbf{B}^{-})\}$, where $\mathbf{B}^{-} = [-57.833, 0, 0, 0, 0, 0]^T$, $\mathbf{B}^{+} = [-10.947, 0, 0, 0, 0, 0]^T$, $\mathbf{X} = [GA_1, GA_2, GA_3, GA_4, GA_5, GY_1, GY_2, GY_3, GY_4, GY_5]^T$,

$$\mathbf{A}^{-} = \begin{bmatrix} -1 & -1 & -1 & -1 & -1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & -18.93 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & -44.29 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & -17.03 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & -75.71 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & -43.15 \end{bmatrix}, \quad \text{and}$$

$$\mathbf{A}^{+} = \begin{bmatrix} -1 & -1 & -1 & -1 & -1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & -7.57 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & -15.52 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & -17.03 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & -45.42 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & -30.28 \end{bmatrix}.$$

Step 1: Solve the problems $\min_{\Omega_0} \hat{z}_1$ and $\min_{\Omega_0} \hat{z}_2$ and find optimal values, where

$$\hat{z}_1 = \sum_{i=1}^{5} (1000 GA_i \times \overleftrightarrow{GHGo_i} \times 365 \times 20 + GY_i \times \overleftrightarrow{GHGc_i}),$$

$$\hat{z}_2 = \sum_{i=1}^{5} (1000 GA_i \times \overleftrightarrow{GC_i} \times 365 \times 20 + GY_i \times F_i),$$

$\overleftrightarrow{GHGo_i} \in \{GHGo_i^-, GHGo_i^+\}$, $\overleftrightarrow{GHGc_i} \in \{GHGc_i^-, GHGc_i^+\}$, $\overleftrightarrow{GC_i} \in \{GC_i^-, GC_i^+\}$. Let $\hat{z}_{1opt}$'s be the optimal values of problems $\min_{\Omega_0} \hat{z}_1$ and $\hat{z}_{2opt}$'s be those of problems $\min_{\Omega_0} \hat{z}_2$

Step 2: Specify $\boldsymbol{\alpha}$ matrix and solve the problems $\min_{\Omega_\alpha \cap \mathbf{R}_1} r_1$ and $\min_{\Omega_\alpha \cap \mathbf{R}_2} r_2$, where $\mathbf{R}_1 = \{r_1, \mathbf{X} \mid r_1 \geq \hat{z}_1 - \hat{z}_{1opt}\}$ and $\mathbf{R}_1 = \{r_2, \mathbf{X} \mid r_2 \geq \hat{z}_2 - \hat{z}_{2opt}\}$. Let $\mathbf{X}_1^{\text{opt}}(\boldsymbol{\alpha})$ and $r_1^{\text{opt}}(\mathbf{X}_1^{\text{opt}}(\boldsymbol{\alpha}), \boldsymbol{\alpha})$ be the optimal solution and value of the problem $\min_{\Omega_\alpha \cap \mathbf{R}_1} r_1$ and $\mathbf{X}_2^{\text{opt}}(\boldsymbol{\alpha})$ be those of the problem $\min_{\Omega_\alpha \cap \mathbf{R}_2} r_2$.

Step 3: Form a payoff table.

	r_1	r_2
$\mathbf{X}_1^{\text{opt}}(\boldsymbol{\alpha})$	$r_1^{\text{opt}}(\mathbf{X}_1^{\text{opt}}(\boldsymbol{\alpha}), \boldsymbol{\alpha})$	$r_2\ (\mathbf{X}_1^{\text{opt}}(\boldsymbol{\alpha}), \boldsymbol{\alpha})$
$\mathbf{X}_2^{\text{opt}}(\boldsymbol{\alpha})$	$r_1\ (\mathbf{X}_2^{\text{opt}}(\boldsymbol{\alpha}), \boldsymbol{\alpha})$	$r_2^{\text{opt}}(\mathbf{X}_2^{\text{opt}}(\boldsymbol{\alpha}), \boldsymbol{\alpha})$

Step 4: Solve the problem $\min_{\Omega_\alpha \cap \mathbf{R}_1 \cap \mathbf{R}_2 \cap \mathbf{R}_r} \Gamma$ and find the NMMR solution, where

$$\mathbf{R}_r = \{\Gamma, r_1, r_2, \mathbf{X} \mid \Gamma \geq \frac{r_1 - r_1^{\text{opt}}(\mathbf{X}_1^{\text{opt}}(\boldsymbol{\alpha}), \boldsymbol{\alpha})}{r_1\ (\mathbf{X}_2^{\text{opt}}(\boldsymbol{\alpha}), \boldsymbol{\alpha}) - r_1^{\text{opt}}(\mathbf{X}_1^{\text{opt}}(\boldsymbol{\alpha}), \boldsymbol{\alpha})} \text{ and } \Gamma \geq \frac{r_2 - r_2^{\text{opt}}(\mathbf{X}_2^{\text{opt}}(\boldsymbol{\alpha}), \boldsymbol{\alpha})}{r_2\ (\mathbf{X}_1^{\text{opt}}(\boldsymbol{\alpha}), \boldsymbol{\alpha}) - r_2^{\text{opt}}(\mathbf{X}_2^{\text{opt}}(\boldsymbol{\alpha}), \boldsymbol{\alpha})}\}\ .$$

If the solution is acceptable by decision maker, the obtained solution is the final solution. If not, go to Step 5.

Step 5: Specify a different $\boldsymbol{\alpha}$ matrix and repeat from Step 2 to Step 4.

CHAPTER FIVE: RESEARCH RESULTS

5.1 System Dynamics Modeling For Domestic Water Demand Under Changing Economy

In the system dynamics model, the uncertainties embedded in parameters or equations being derived associated with the two driving forces are worthy of being further explored by sensitivity analysis. It helps gain a better understanding as to how reliable the estimated water demand could be under the uncertain economic impact given that the domestic water demand in the study period is highly nonlinear in response to the changing macroeconomic environments. Therefore, small offset on the two driving forces were setup in order to keep the trend so that the offset demand curved would be in a similar pattern as the base model as shown in Figure 5-1. In the sensitivity analysis, the unemployment rate (UR) and the average annual income (AAI) are offset by ±5% and ±2%, respectively. Having this carried out, the resultant impact on domestic water demand can be realized and illustrated in Figure 5-2 with respect to the upper and lower bounds of the estimated water demand in response to the offset unemployment rate and annual average income from 2003 to 2009. The vertical solid lines represent the intervals of water demand, which are caused by the fluctuations or uncertainties associated with the changing macroeconomic environments. The triangle marks stand for the estimated values of the base model relative to those fluctuated values above and below them.

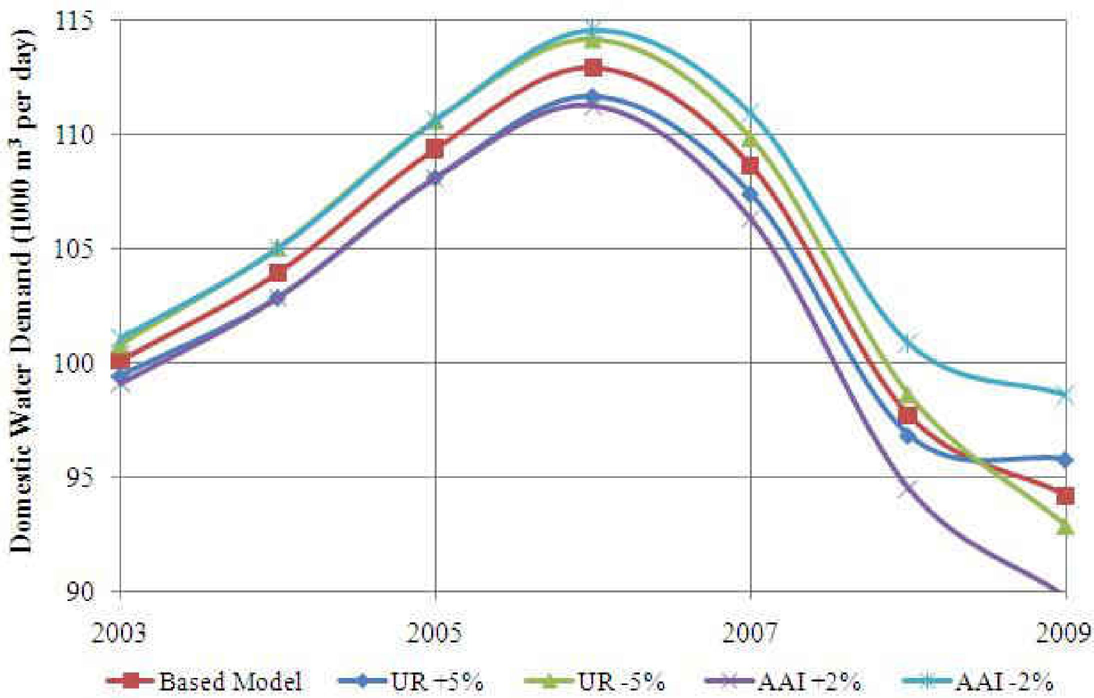


Figure 5-1 Model outputs with the offset unemployment rate and average annual income

From the sensitivity analysis, it is indicative that the subtle change of unemployment rate results in a more change in the estimated domestic water demand. Such a fluctuation does not change the estimated water demand curve pattern, however. Besides, the subtle change of average annual income may result in a greater impact to the water demand compared to the impact of unemployment rate fluctuations. Such an impact to the water demand due to the uncertain average annual income becomes obvious when the unemployment rate is in a high level (e.g. year 2008 and 2009). It is noticeable that the increase of average annual income may positively affect the real estate market and further affect the population growth and migration. Yet, the phenomenon that the estimated water demand declines in response to the average annual income increase is mainly caused by the total population decrease which is primary due to the change of net immigration rate. Therefore, it may lead to a conclusion that the proposed system dynamics model is less sensitive to the uncertainties of unemployment rate than the average annual income.

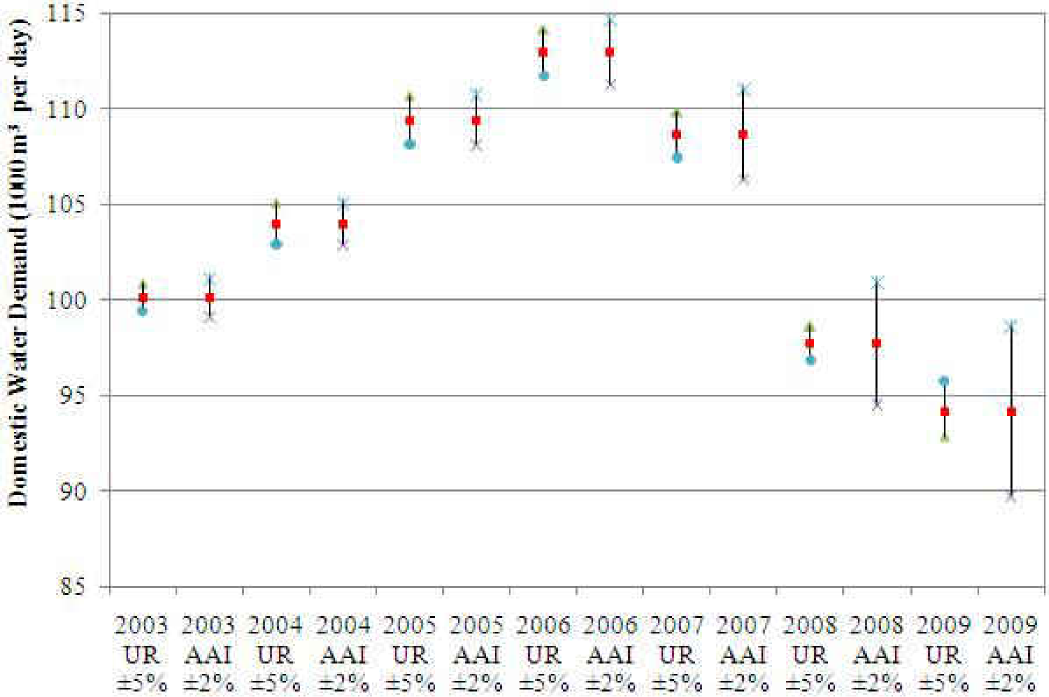


Figure 5-2 Sensitivity analysis of domestic water demand

5.2 Carbon Footprint Evaluation For A Water Infrastructure System

5.2.1 Carbon Footprints In Construction Phase

By applying the methods described in Sections 4.2.3.1 and 4.2.3.2, CO_2 equivalent emissions in the raw material acquisition stage and in the facility construction stage are determined. The results are shown in Table 5-1 and Table 5-2, respectively. The options for transferred water use permit (e.g., alternatives #10, #11, and #12) bear no burden of carbon footprint in the construction phase since no new facility or piping is needed due to the nature of these alternatives. Those transferred water credits are mainly from existing water sources, transported using existing piping, treated at the existing WTP, and delivered to consumers by existing piping network. Nothing needs to be changed when such options are adopted.

Table 5-1 Carbon footprint in raw material acquisition stage (Process ①)

Column no.	1	2	3	4	5	6
Alternative number	Concrete required ($10^3 m^3$)	Energy required for concrete* (J)	Steel required ($10^3 t$)	Energy required for enforced steel** (J)	Diesel required△ (L)	CO_2 equivalent emissions△ (g)
1	0	0	4.25	6.72×10^{13}	0	1.31×10^{10}
2	0	0	6.17	9.76×10^{13}	0	1.90×10^{10}
3	0	0	4.50	7.12×10^{13}	0	1.39×10^{10}
4	0	0	8.89	1.41×10^{14}	0	2.75×10^{10}
5	0	0	7.36	1.17×10^{14}	0	2.27×10^{10}
6	0	0	0	0	160000	4.37×10^{8}
7	0	0	5.77	9.13×10^{13}	320000	1.87×10^{10}
8	0	0	19.26	3.05×10^{14}	480000	6.08×10^{10}
9	0	0	10.02	1.95×10^{14}	320000	3.18×10^{10}
10	0	0	0	0	0	0
11	0	0	0	0	0	0
12	0	0	0	0	0	0
13	9.174	1.90×10^{13}	39.24	6.21×10^{14}	480000	1.26×10^{11}
14	3.822	7.91×10^{12}	58.84	9.31×10^{14}	320000	1.84×10^{11}
15	3.822	7.91×10^{12}	23.05	3.65×10^{14}	480000	7.40×10^{10}
16	3.822	7.91×10^{12}	23.05	3.65×10^{14}	480000	7.40×10^{10}
17	2.866	5.93×10^{12}	14.20	2.25×10^{14}	320000	4.59×10^{10}
18	2.676	5.54×10^{12}	10.54	1.67×10^{14}	320000	3.45×10^{10}
19	2.676	5.54×10^{12}	12.44	1.97×10^{14}	320000	4.04×10^{10}
20	1.912	3.96×10^{12}	13.58	2.15×10^{14}	0	4.27×10^{10}

Note: 1 joule = 2.7778×10^{-7} kWh or 1 Wh = 3600 J

* Estimations in (2) = estimations in (1) × 2.07 $GJ\cdot m^{-3}$ (Struble and Godfrey, 2004)

** Estimations in (4) = estimations in (3) ×15.83 $MJ\cdot kg^{-1}$ (Stubbles, 2000)

△Estimations in (6) = [estimations in (2) + (4)]×702 $g\cdot kWh^{-1}$+ estimation in (5) × 2.73 $kg\cdot L^{-1}$

Table 5-2 Carbon footprint in facility construction stage (Process ②)

Column no.	1	2	3	4	5	6
Alternative number	Earth structural system for reservoirs (km^2)	CO_2 equivalent emissions for reservoirs* (g)	Concrete structural systems for WTPs (m^2)	Steel assemblies for WTPs (m^2)	CO_2 equivalent emissions for WTPs** (g)	Total CO_2 equivalent emissions△ (g)
1	0	0	0	0	0	0
2	0	0	0	0	0	0
3	0	0	0	0	0	0
4	0	0	0	0	0	0
5	0	0	0	0	0	0
6	0.92	1.83×10^{10}	0	0	0	1.83×10^{10}
7	1.83	3.76×10^{10}	0	0	0	3.67×10^{10}
8	2.75	5.50×10^{10}	0	0	0	5.50×10^{10}
9	1.83	3.67×10^{10}	0	0	0	3.67×10^{10}
10	0	0	0	0	0	0
11	0	0	0	0	0	0
12	0	0	0	0	0	0
13	2.75	5.50×10^{10}	91740	15000	1.85×10^{9}	5.69×10^{10}
14	1.83	3.67×10^{10}	38220	6250	7.71×10^{8}	3.75×10^{10}
15	2.75	5.50×10^{10}	38220	6250	7.71×10^{8}	5.58×10^{10}
16	2.75	5.50×10^{10}	38220	6250	7.71×10^{8}	5.58×10^{10}
17	1.83	3.67×10^{10}	28660	4690	5.78×10^{8}	3.73×10^{10}
18	1.83	3.67×10^{10}	26760	4380	5.40×10^{8}	3.72×10^{10}
19	1.83	3.67×10^{10}	26760	4380	5.40×10^{8}	3.72×10^{10}
20	0	0	19120	3130	3.86×10^{8}	3.86×10^{8}

Assumptions: $1m^2$ requires $0.1m^3$ concrete or 0.1t steel for WTP and $1m^3$ earth for reservoirs.
* Estimations in (2) = estimations in (1) ×20 $kg{\cdot}m^{-2}$ (Cole, 1998)
** Estimations in (5) = estimations in (3) × 20 $kg{\cdot}m^{-2}$ + estimations in (4) × 1 $kg{\cdot}m^{-2}$ (Cole, 1998)
△ Estimations in (6) = estimations in (2) + estimations in (5)

5.2.2 Carbon Footprints In Operational Phase

The operational phases include production, use, and recycle processes. By applying the methods described in Section 4.2.4.1, we may estimate the CO_2 equivalent emissions in the raw water transportation stage (see Table 5-3). Table 5-4 further summarizes the CO_2 equivalent emissions in the raw water treatment stage (process ④), potable water distribution stage (process ⑤), sewage and wastewater collection stage (process ⑥), wastewater treatment stage (process

⑦), reclaimed water reuse and discharge stages (process ⑧ and ⑨). The process numbers used above are defined by Figure 3-3. Those CO_2 equivalent emissions in the operational phase are variable as a function of the volume of water supplied and serviced. The calculated CO_2 equivalent emissions are rounded to the nearest unit of gram per cubic meter water produced.

Table 5-3 Carbon footprint in raw water transportation stage (Process ③)

Column no.	1	2	3
Alternative number	*D* (km)	Energy consumption ($kWh\cdot m^{-3}$)	CO_2 equivalent emissions ($g\cdot m^{-3}$)
1	22.85	1.69	1190
2	29.29	2.17	1525
3	25.43	1.89	1324
4	32.83	2.43	1709
5	29.93	2.22	1558
6	negligible	negligible	negligible
7	15.93	1.18	829
8	49.73	3.69	2589
9	37.82	2.80	1969
10	negligible	negligible	negligible
11	negligible	negligible	negligible
12	negligible	negligible	negligible
13	90.93	6.74	4734
14	109.44	8.12	5697
15	42.16	3.13	2195
16	42.16	3.13	2195
17	29.77	2.21	1550
18	29.77	2.21	1550
19	29.77	2.21	1550
20	35.08	2.60	1827

Estimates in (2) = $7.1347 \times 2.71818^{2.3413} \times$ estimates in (1) / 1000 (Gabi database)
Estimates in (3) = estimates in (2) × 702 $g\cdot kWh^{-1}$ (Energy density of real mixed power grid)

Table 5-4 Carbon footprint estimations in process ④, ⑤, ⑥, ⑦, ⑧ and ⑨

Alternative Number	CO_2 equivalent emissions ($g\cdot m^{-3}$)					
	Process ④	Process ⑤	Process ⑥	Process ⑦	Process ⑧	Process ⑨
1 ~ 19	70	602	246	238	0	0
20	365					

5.2.3 Carbon Footprint Analysis

The carbon-footprint analysis in all phases of the twenty alternatives were estimated and compared with each other in terms of CO_2 equivalent emissions within a 20-year time period (2011–2030). Estimated carbon footprints are summarized in Table 5-5. Averages of the total CO_2 equivalent emissions and unit costs of those alternatives are also listed for comparisons. The carbon-footprint analysis was also carried out by using a Gabi® 4 model that may automate the generation of the same results as shown in Table 5-5. A screenshot of Gabi® model is shown in Figure 5-3. In the Gabi® 4 model, all processes and their corresponding CO_2 equivalent emissions were set according to Section 3.2 and Figure 3-3. With this model, calculations of CO_2 equivalent emissions become convenient once the data of the processes have to be updated at any time. Besides, the Gabi® 4 model provides the possibility to perform sensitivity analysis related to any one of relevant parameters (e.g., distance, rate of CO_2 equivalents, etc.) or collective changes of many parameter values simultaneously.

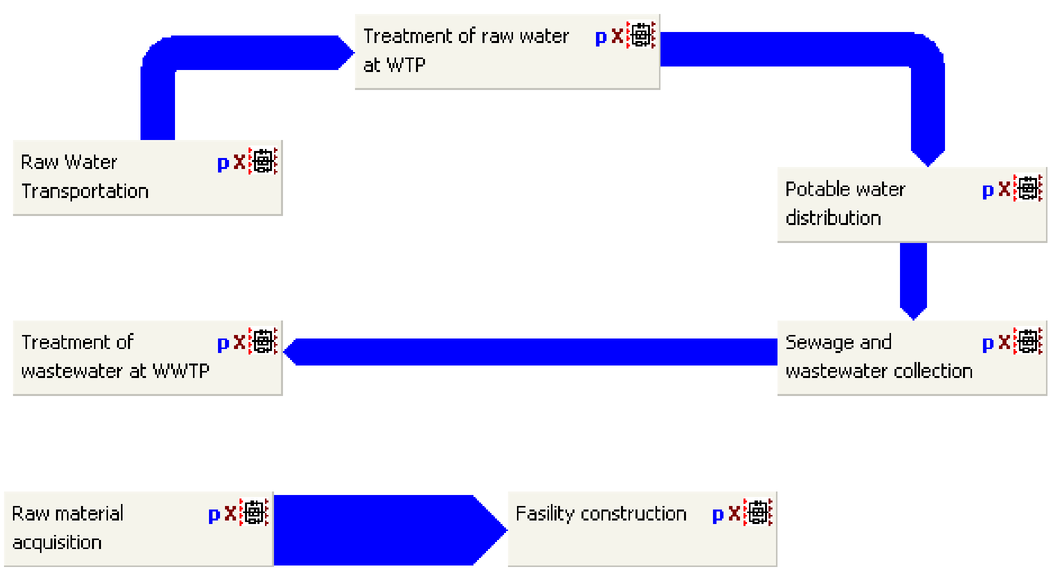


Figure 5-3 A screenshot of Gabi® 4 carbon-footprint analysis

Table 5-5 Results of carbon-footprint analysis

	Alternative Number	CO_2 equivalent emissions in construction phase△ (g)	CO_2 equivalent emissions in use phase△△ ($g\cdot m^{-3}$)	20-year-capacity ($10^3 m^3$)	Total CO_2 equivalent emissions (g)	Group average of total CO_2 equivalent emissions (g)	Group average of unit cost ($\$\cdot m^{-3}$)
Ground water	1	1.31×10^{10}	2346	59933	1.54×10^{11}	2.42×10^{11}	0.42
	2	1.90×10^{10}	2681	82928	2.41×10^{11}		
	3	1.39×10^{10}	2480	55261	1.51×10^{11}		
	4	2.75×10^{10}	2865	138189	4.23×10^{11}		
Surface water	5	2.27×10^{10}	2714	113296	3.30×10^{11}	5.94×10^{11}	0.82
	6	1.88×10^{10}	1156	323317	3.93×10^{11}		
	7	5.54×10^{10}	1985	254259	5.60×10^{11}		
	8	1.16×10^{11}	3745	292949	1.21×10^{12}		
	9	6.85×10^{10}	3125	129867	4.74×10^{11}		
WUP*	10	Negligible	1156	124319	1.44×10^{11}	1.44×10^{11}	0.54
	11	Negligible	1156	negligible	Negligible		
	12	Negligible	1156	negligible	Negligible		
Regional water	13	1.83×10^{11}	5890	331566	2.14×10^{12}	2.26×10^{12}	0.58
	14	2.22×10^{11}	6853	552683	4.01×10^{12}		
	15	1.30×10^{11}	3351	552683	1.98×10^{12}		
	16	1.30×10^{11}	3351	552683	1.98×10^{12}		
	17	8.31×10^{10}	2706	414494	1.20×10^{12}		
Others	18	7.17×10^{10}	2706	221044	6.70×10^{11}	8.50×10^{11}	0.74
	19	7.76×10^{10}	2706	314995	9.30×10^{11}		
	20	4.31×10^{10}	3278	276305	9.49×10^{11}		

*WUP = Water Use Permit. The capacities of the alternative #11 and #12 are currently not available according to the work plan (Manatee County Board of County Commissioners, 2008). Thus, CO_2 equivalent emissions in the operational phase associated with the alternative #11 and #12 are set to zero temporarily. The average of total CO_2 equivalent emissions associated with the WUP group does not take alternative #11 and #12 into consideration.

△Process ① + ②

△△Process ③+④+⑤+⑥+⑦+⑧+⑨

5.2.4 Sensitivity Analysis

It is well known that limitations of data quality and difficulties to assess uncertainties on the variables may lead to incorrect or sometimes misleading decisions (US EPA, 1995). Uncertainties can be reduced by better understanding of data sources, based on how the carbon footprints and costs are derived.

5.2.4.1 Types And Sources Of Uncertainty

A comprehensive survey (Bjoerklund, 2002) on types and sources of uncertainty may also be applicable in our carbon footprint analysis. These uncertainties are summarized in Table 5-6. Major categories of uncertainties include data accuracy (e.g. distance measurement in Google Earth®), unrepresentative data (e.g. using similar WTP and WWTP processes data), and uncertainty due to choices (e.g. choice of assumptions), all of which can affect the carbon footprint calculations. Under the guidelines of ISO standard (ISO 14043, 2000) we performed the sensitivity analysis to identify the most significant uncertainties related to the assumptions and data in the present study. Final outcome may be used to help clarify the efforts in decision analysis in which key issues with high uncertainty should be highlighted in final decision making.

Table 5-6 Types and sources of uncertainty

Types of uncertainty	**Remark**
Data inaccuracy	It is caused by random error which results from imperfections in the measurement.
Data gaps	It is caused by missing parameter values.
Unrepresentative data	It may avoid data gaps. But, data from similar processes may be of unrepresentative age, geographical origin, or technical performance.
Model uncertainty	It is caused by simplifications of aspects that cannot be modeled within the analysis structure.
Uncertainty due to choices	Choices of system boundaries, marginal or average data, and allocation rules are also a source of uncertainty because there is often not one single correct choice.
Epistemological uncertainty	It is caused by lack of knowledge on system behavior.
Mistakes	Mistakes are also a source of uncertainty, seldom acknowledged and vey difficult to assess (Finnveden, 2000).
Estimation of uncertainty	Estimation of all types of uncertainty is in itself a source of uncertainty.

Source: (Bjoerklund, 2002)

5.2.4.2 Sensitivity Analysis Results

Some key input parameters can be highlighted for sensitivity analysis following the order of construction, production, use and recycle phases (Table 5-7), in which the Gabi® 4.0 model expressed in Figure 5-3 is repeatedly carried out. Because the range of variation for each input parameter is largely unknown, subjective selection of ±5% from the base value is applied in this sensitivity analysis. By comparing the level of changes of GWP, the important impact of each input parameter on decision analysis can be characterized. The results of sensitivity analysis correspond to the percent change in terms of total CO_2 equivalent emissions over the focused time period due to ±5% change in each of the individual input parameter can be summarized in Table 5-8.). In this context, the variance of raw material requirement (e.g steel and cement) can only cause an insignificant fraction of GWP fluctuations in term of the GHG emissions in the life cycle that we focused on. The most influential factors affecting the total GHG emissions are from operational phrase. The uncertainties associated with the amount of potable water demand and the distance for water transportations are among the biggest contributors to the uncertainty of total GHG emissions. Thus, acquisition and estimation of these parameters as model inputs are the most important as they are viewed as hotspots in terms of GWP within the prescribed system boundary. Further refinement of uncertainties associated with energy or GHG intensity of WTP or WWTP may also improve the reliability of the optimization analysis; however, they are less significant factors than potable water demand and water transportation distances.

Table 5-7 The selection of inputs parameters for sensitivity analysis

Input parameter	**Uncertainty type**	**Remark**
Construction phase		
Need of Steel	Uncertainty due to choices	The need of steel and cement is assumed to be proportional to the length of piping, capacity of new WTP and size of new reservoir
Need of Cement		
Production, use and recycle phases		
Distance of raw water transportation	Data inaccuracy	The distance is estimated by either actual piping route (e.g. regional water options) measured by Google Earth® or the suggested driving route by Google Map® between the source water location and the Manatee WTP.
Distance of potable water distribution	Data inaccuracy	This distance is estimated by using method in Section 5.3.1
Distance of waste water collection	Data inaccuracy	This distance is estimated by using method in Section 5.3.2
Energy intensity of raw water treatment	Unrepresentative data	Data from other similar processes are used
GHG intensity of wastewater treatment	Unrepresentative data	Data from other similar processes are used
Daily water credit	Uncertainty due to choices	Average value is selected

Table 5-8 The results of sensitivity analysis

Results of sensitivity analysis					
±5% Alternative	**1**	**2**	**3**	**4**	**5**
Daily water credit	4.57%	4.61%	4.54%	4.68%	4.66%
Distance of raw water transportation	2.32%	2.62%	2.42%	2.79%	2.67%
Distance of portable water distribution	1.17%	1.03%	1.1%	0.983%	1.03%
Distance of waste water collection	0.48%	0.423%	0.45%	0.402%	0.422%
Energy intensity of raw water treatment	0.137%	0.121%	0.128%	0.115%	0.12%
GHG intensity of wastewater treatment	0.463%	0.408%	0.435%	0.388%	0.408%
Need of Cement	0	0	0	0	0
Need of Steel	0.427%	0.395%	0.46%	0.324%	0.344%
±5% Alternative	**6**	**7**	**8**	**9**	**10**
Daily water credit	4.76%	4.51%	4.52%	4.28%	5.00%

Results of sensitivity analysis					
Distance of raw water transportation	0	1.88%	3.13%	2.7%	0
Distance of portable water distribution	2.48%	1.37%	0.727%	0.825%	2.6%
Distance of waste water collection	1.01%	0.559%	0.297%	0.337%	1.06%
Energy intensity of raw water treatment	0.289%	0.159%	0.085%	0.096%	0.304%
GHG intensity of wastewater treatment	0.978%	0.539%	0.287%	0.325%	1.03%
Need of Cement	0	0	0	0	0
Need of Steel	0	0.159%	0.245%	0.326%	0
±5% Alternative	**11**	**12**	**13**	**14**	**15**
Daily water credit	0	0	4.57%	4.72%	4.67%
Distance of raw water transportation	0	0	3.67%	3.93%	3.06%
Distance of portable water distribution	0	0	0.467%	0.415%	0.84%
Distance of waste water collection	0	0	0.191%	0.17%	0.343%
Energy intensity of raw water treatment	0	0	0.055%	0.048%	0.098%
GHG intensity of wastewater treatment	0	0	0.184%	0.164%	0.331%
Need of Cement	0	0	0.013%	0.003%	0.006%
Need of Steel	0	0	0.284%	0.227%	0.18%
±5% Alternative	**16**	**17**	**18**	**19**	**20**
Daily water credit	4.67%	4.66%	4.47%	4.58%	4.77%
Distance of raw water transportation	3.06%	2.67%	2.56%	2.63%	2.66%
Distance of portable water distribution	0.84%	1.04%	0.994%	1.02%	0.877%
Distance of waste water collection	0.343%	0.423%	0.406%	0.417%	0.358%
Energy intensity of raw water treatment	0.098%	0.121%	0.116%	0.119%	0.532%
GHG intensity of wastewater treatment	0.331%	0.409%	0.392%	0.402%	0.346%
Need of Cement	0.006%	0.007%	0.012%	0.009%	0.006%
Need of Steel	0.18%	0.182%	0.243%	0.206%	0.221%

Note: The values in the cells present for the standard deviation of total GHG emissions in a 20 year period from 2011 to 2030.

5.3 Multiobjective Programming For Water System Optimization

5.3.1 Pareto Optimal Solutions

A Pareto Optimal solution is one of the feasible solutions that no other feasible solution may perform better than it in terms of both objectives at the same time. Thus, a non-Pareto optimal solution is not interested for decision makers because there must be at least one solution in the Pareto optimal set that will perform better in terms of both cost and CO_2 equivalent emissions. With this understanding, the solution set $\left\{(Z_1^m, Z_2^m) \middle| \text{all } m\right\}$ is the approximate Pareto optimal frontier with which we can plot all the Pareto optimal solutions in the objective space. These "Pareto Optimal" solutions present trade-offs with each other along the frontier. That means, if one Pareto optimal solution performs worse in one objective, it must performs better in terms of the other objective in trade-off. Therefore, in the objective space, the Pareto optimal set in our case would always located along the most lower left side of the entire feasible solution set with respect to the given ideal solution situated at the lower left corner in Figure 5-4. Figure 5-4 plots the Pareto Optimal frontiers of the three cases (e.g., n = 1, 2, and 3).

Along the Pareto Optimal frontier, the term of '*A* dominates *B*' means that there is no solution in B which is absolutely better than any one of the solutions in *A* in terms of both objective functions. In other words, the frontier of the solution set of *A* is closer to the lower left corner of the objective space compared with the frontier of the solution set of *B*. Because both objective functions are defined for minimization, the ideal solution is located in the lower left corner of the objective space. Thus, as it can be seen from Figure 5-4, the Pareto Optimal solution dominates in the order of n=3 > n=2 > n=1. Apparently, with more water supply alternatives implemented in one time stage, more options are available for the County to improve the long-term performance of the solutions in terms of both economic efficiencies and carbon footprints.

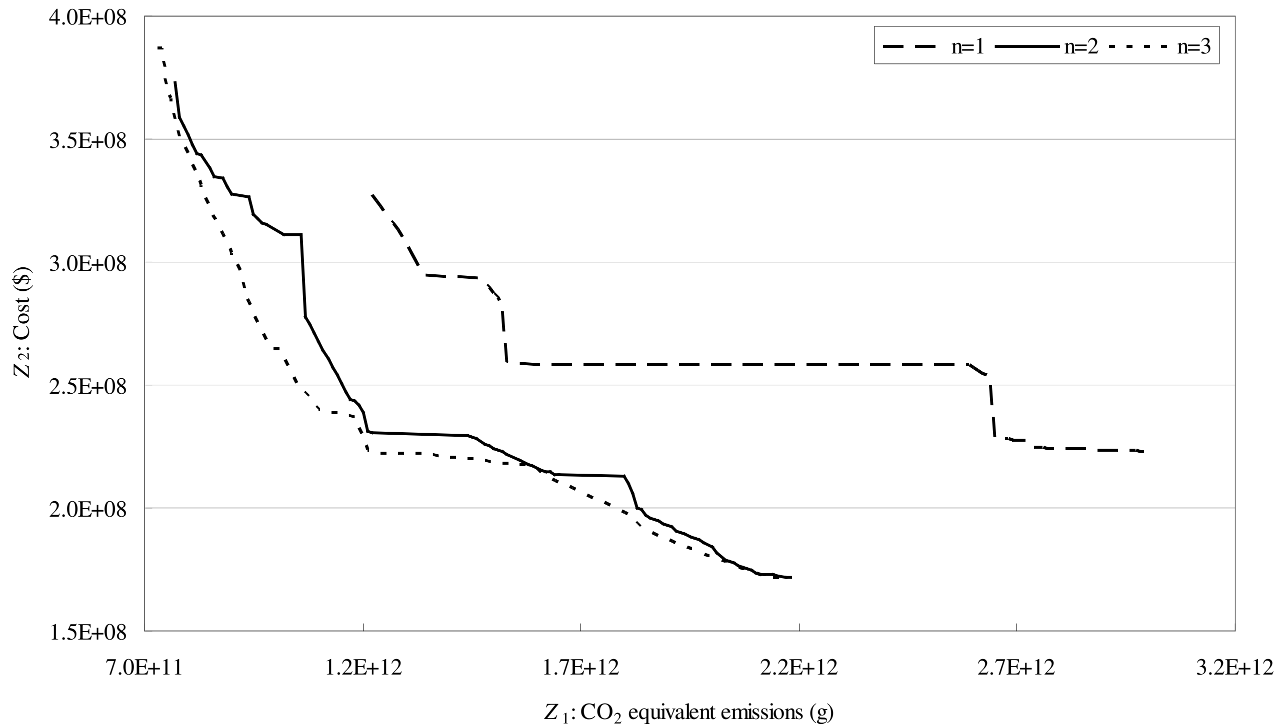


Figure 5-4 Solution space of the multiobjective programming model

5.3.2 Sensitivity Analysis

Since municipal water demand projection is highly uncertain, a sensitivity analysis was conducted to evaluate the modeling effect of the uncertainty. The expected water demand was assumed to contain a ±10% variance, for which the best (optimistic) and the worst (pessimistic) cases were re-examined by setting water demand D_i (i = 1, 2, 3, 4) as $0.9D_i$ and $1.1D_i$ in the multiobjective programming. For n = 1, the Pareto Optimal solution sets are solved for the best case of $0.9D_i$ (D_1 = 172.97, D_2 = 188.23, D_3 = 190.65, and D_4 = 210.99) and the worst case of $1.1D_i$ (D_1 = 211.41, D_2 = 230.05, D_3 = 233.01, and D_4 = 257.87). The results are plotted in Figure 5-5. Apparently, the Pareto Optimal frontier remains unchanged. In other words, the frontier is closer to the lower left corner in the best case than that in the base case; however, the frontier in the base case is closer to the lower left corner than that of the worst case. In fact, the 10% uncertainty in water demand projection confines optimization sequence to the same solution.

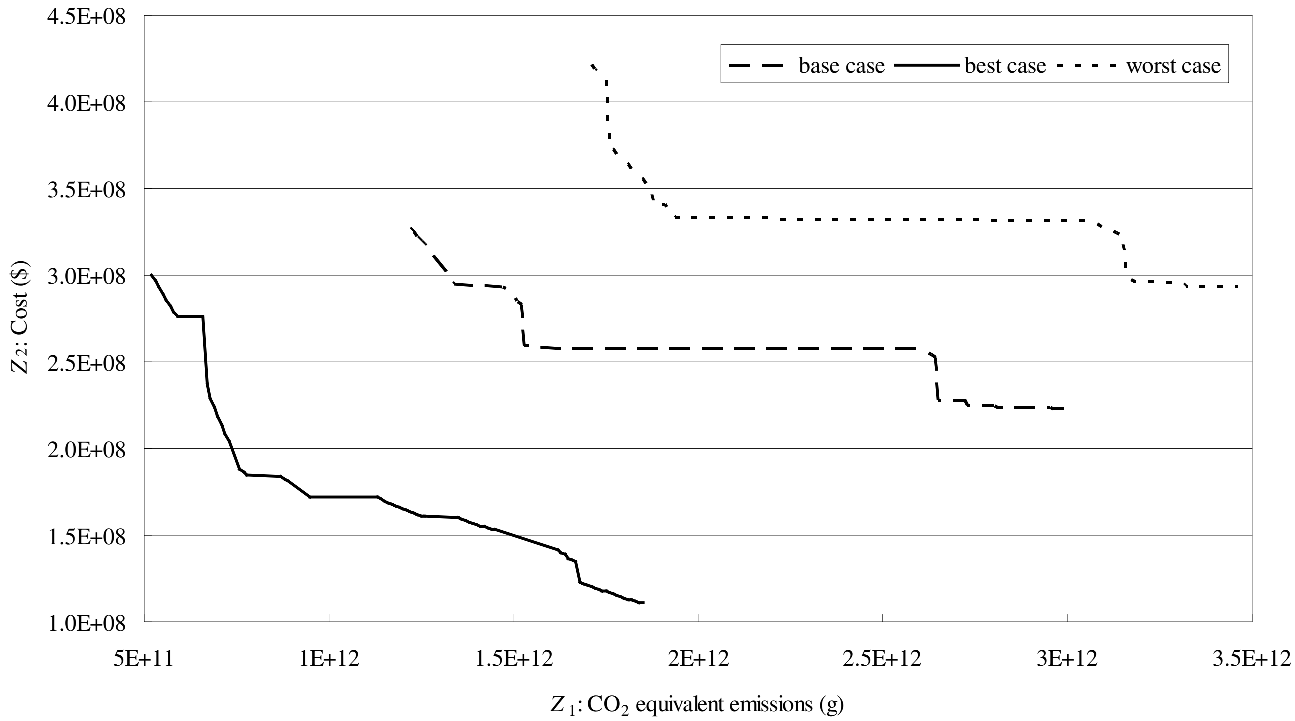


Figure 5-5 optimal solution sets of the three water demand cases under uncertainties

In order to find the best compromised solutions in all the three cases by a comparative approach, we have to normalize the two objective functions by setting them into the same scale between 0 and 1. Such a normalization scheme can be described by Equations 5-1 and 5-2 where where NZ_1 and NZ_2 stand for the normalized values of Z_1 and Z_2, respectively.

$$NZ_1 = \frac{Z_1 - Z_1^{\min}}{Z_1^{\max} - Z_1^{\min}} \tag{5-1}$$

$$NZ_2 = \frac{Z_2 - Z_2^{\min}}{Z_2^{\max} - Z_2^{\min}} \tag{5-2}$$

Figure 5-6 illustrates the normalized solution space as a kind of sensitivity of the best and the worst cases within ±10% offset of the forecasted water demand. Both objectives of carbon footprints and total system cost are scaled uniformly between 0 and 1. Graphical illustrations were employed to holistically present the best choice of the compromised solution associated with these three cases relative to the ideal solution. A widely accepted definition of such distance is based on Minkowski's L_a mectric (Zeleny, 1973), where $1 \le a \le \infty$.

$$L_a = \left[\sum_{i=1}^{2} w_i (NZ_i)^a \right]^{1/a} \tag{5-3}$$

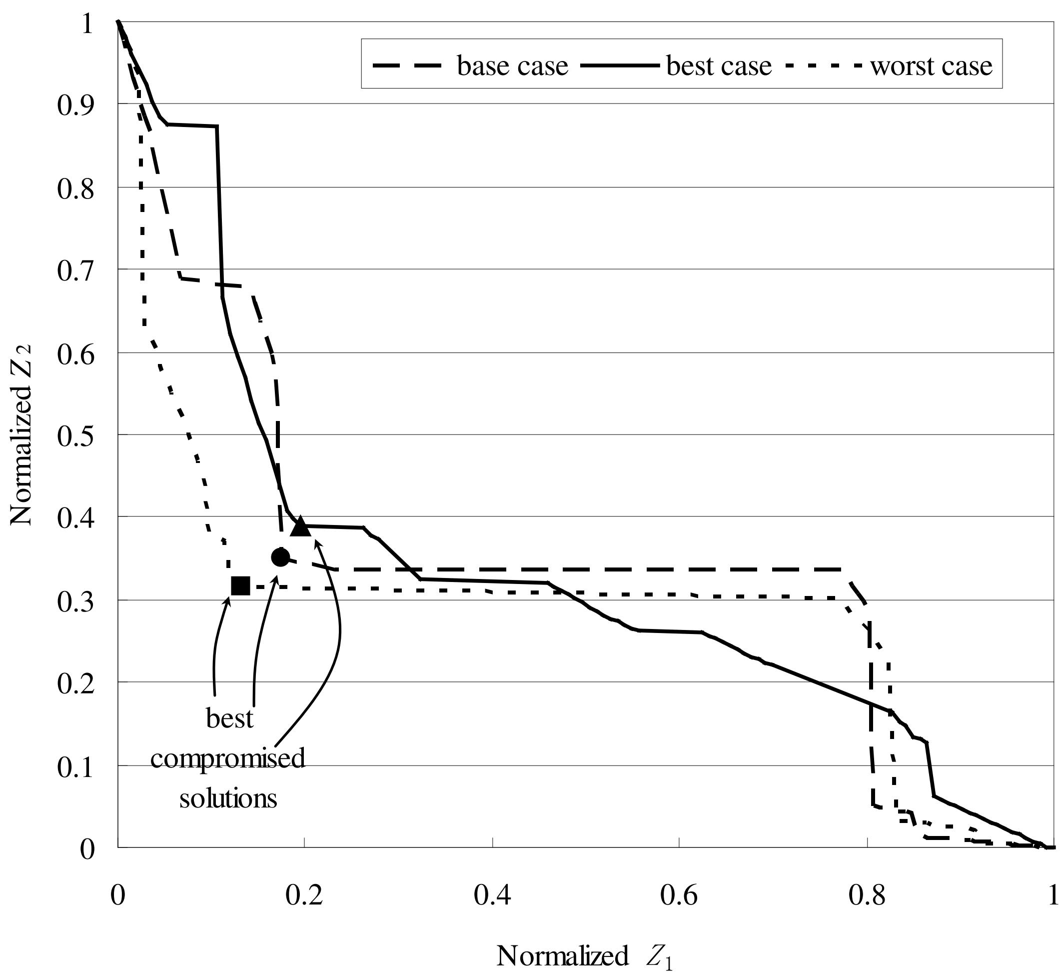


Figure 5-6 The normalized objective space with the three selected cases

Practically, a = 1 implies weighed average of both objectives; a = 2 implies weighted geometric distance between the solution (NZ_1, NZ_2) to the ideal solution (0, 0); and $a = \infty$ implies to minimize the maximum NZ_i when L_a is to be minimized. In our case study, we assume a = 2 and $w_1 = w_2 = 1$. Thus, the best compromised solutions for the three cases can be found and marked in Figure 5-6. These compromised solutions are considered to be the best choices between the two objectives when trade-offs are considered. From Figure 5-7 to Figure 5-10, , it collectively illustrates the details of the optimal facility expansion strategies associated with water distribution solutions for the best compromised solutions in the three cases (worst, base and best). Water distribution solutions for the best and base cases are not shown in Figure 5-7 because no facility expansions are needed in these two cases.

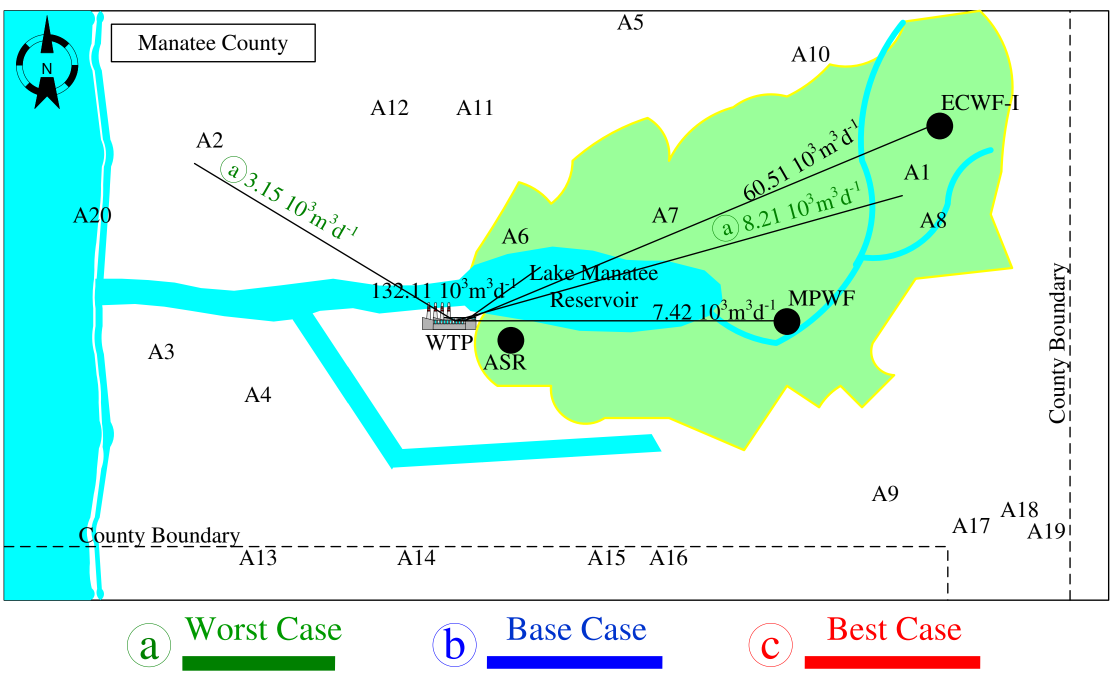


Figure 5-7 Optimal expansion options in time period 1: Year 2011~2015

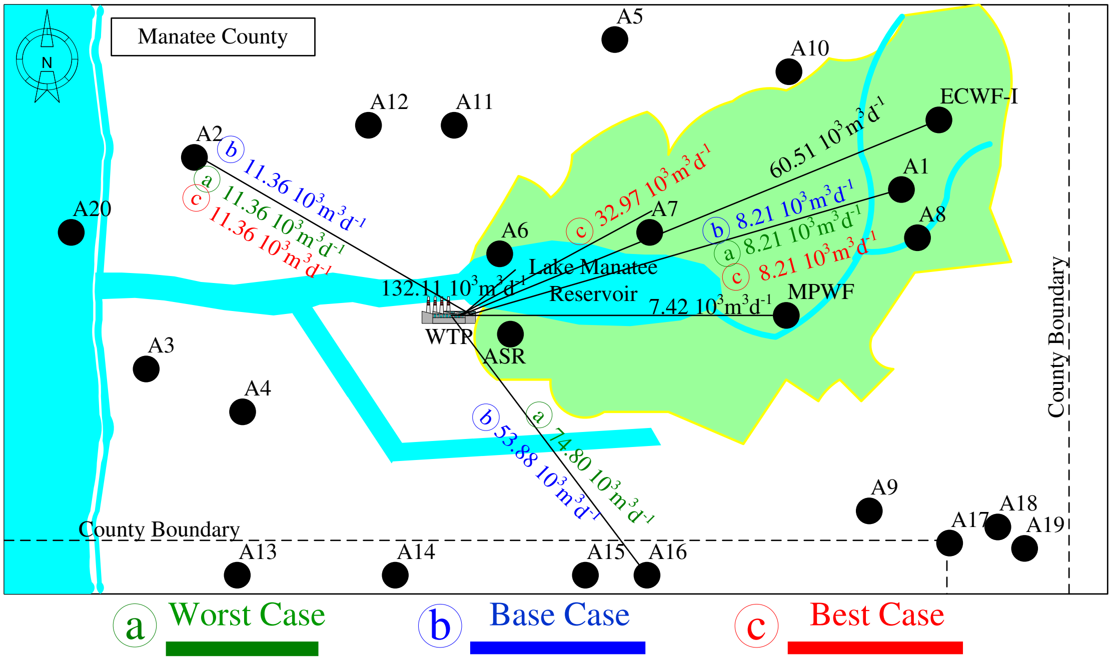


Figure 5-8 Optimal expansion options in time period 2: Year 2016~2020

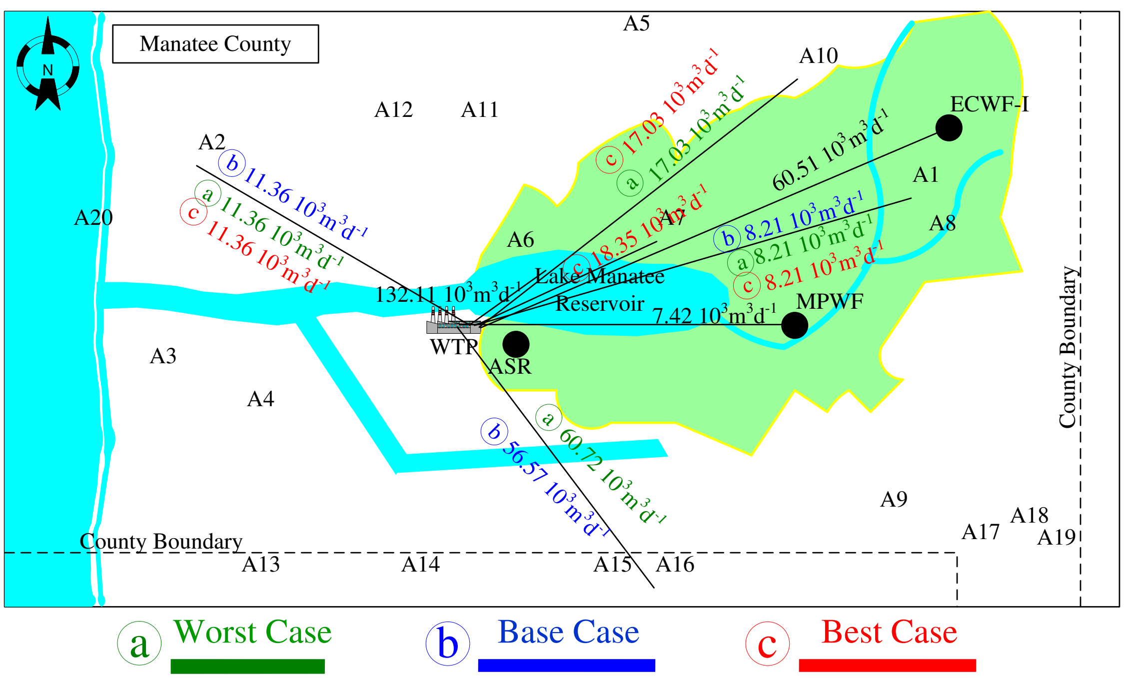


Figure 5-9 Optimal expansion options in time period 3: Year 2021~2025

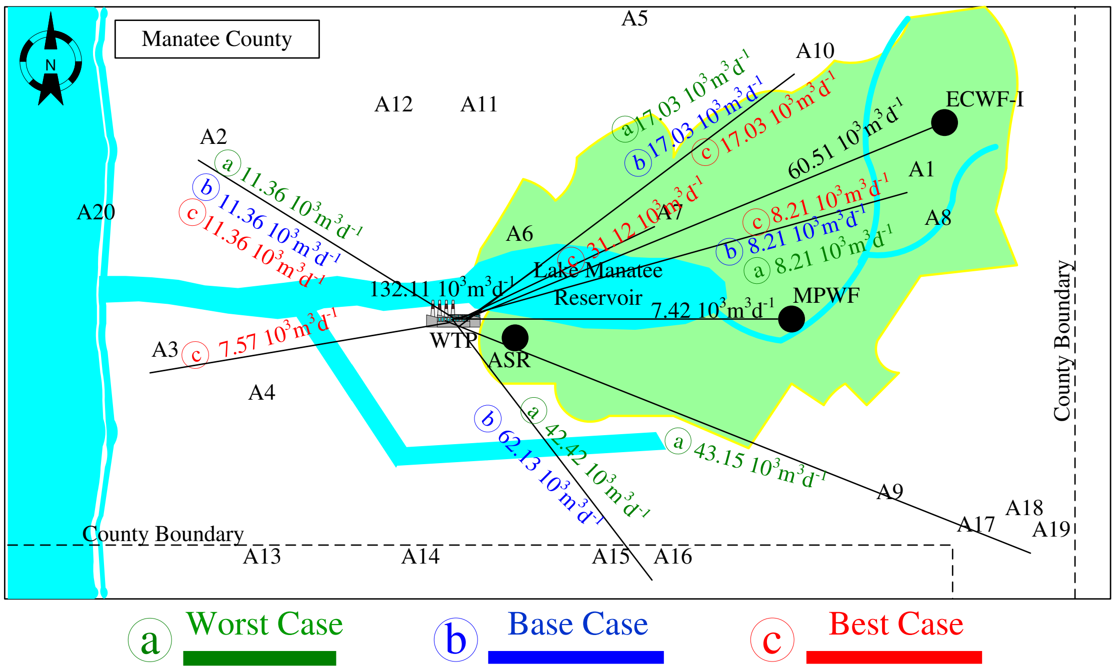


Figure 5-10 Optimal expansion options in time period 4: Year 2026~2030

In the base case and the best case, no more water supply will be required by 2015 so that current water supply is self-sufficient in the first time period. When the forecasted water demand is underestimated or while extra water resources would be needed, MARS-I and MARS-II can provide enough water credit to fulfill the demand from 2016 to 2025. The optimal expansion strategies in this time period are highly dependent on the level of forecasted water demand. Regional water options that offer larger water supply capacity and relatively lower unit costs than other alternatives are needed in both the base case and the worst case. In the best case, regional water supply options must be avoided due to their relatively larger carbon footprints (e.g., long distance shipping) (Table 5-5). Other alternatives available inside the Manatee County may provide better performance for both objectives. As more water demand is anticipated starting from 2026, there will have a variety of optimal expansion strategies and final selection is subject to the decision maker’s preference. In any circumstance, the WUP alternative (e.g. alternative #10) is always preferred in all the cases due to its zero carbon footprint burden and low unit cost. It is indicative that the consideration of objective addressing the concern of carbon footprint did affect the final decision analysis in this case, which confirms our hypothesis in this study.

5.4 Nested Minimax Regret Solution For Decisions Under Uncertainty

The nested minimax solution is a compromising and conservative solution based on decision makers' attitudes to the potential risks to violate non-deterministic constraints. For illustrations, we assume decision makers require equal degree of satisfaction (α) for all the non-deterministic constraints. In other words, the $\boldsymbol{\alpha}$ matrix is assumed to have a single α value as its all diagonal entries. We sweep the α value from 0 to 1 with step size 0.01 and apply the NMMR solution approach described in Section 4.4.2. The first tier absolute regrets for the two objectives are plotted in Figure 5-11. It shows that the first tier absolute regrets are monotone increasing in term of α. Table 5-9 lists the facility expansion recommendations based on the minimax regret criterion in cases of $\alpha = 0.4, 0.6 \text{ and } 0.8$ respectively. As the two objectives are conflicting and a common best minimax regret solution can not be reached, the second tier relative regret solution is needed for the NMMR solution as the final facility expansion strategy. A payoff table is formed in Table 5-10 for the preparation of the NMMR solution method.

Table 5-9 Minimax regret solutions for r_1 and r_2

	min r_1			min r_2		
α	0.4	0.6	0.8	0.4	0.6	0.8
Ground Water Options	12.671	12.114	9.842	9.454	12.114	9.842
Surface Water Options	0	0	0	0	0	0
Transferred Water Options	17.030	17.030	17.03	15.488	17.030	17.03
Regional Water Options	0	0	0	4.760	9.935	21.584
Other Options	0	9.935	21.584	0	0	0

Unit: 1,000 m^3d^{-1}

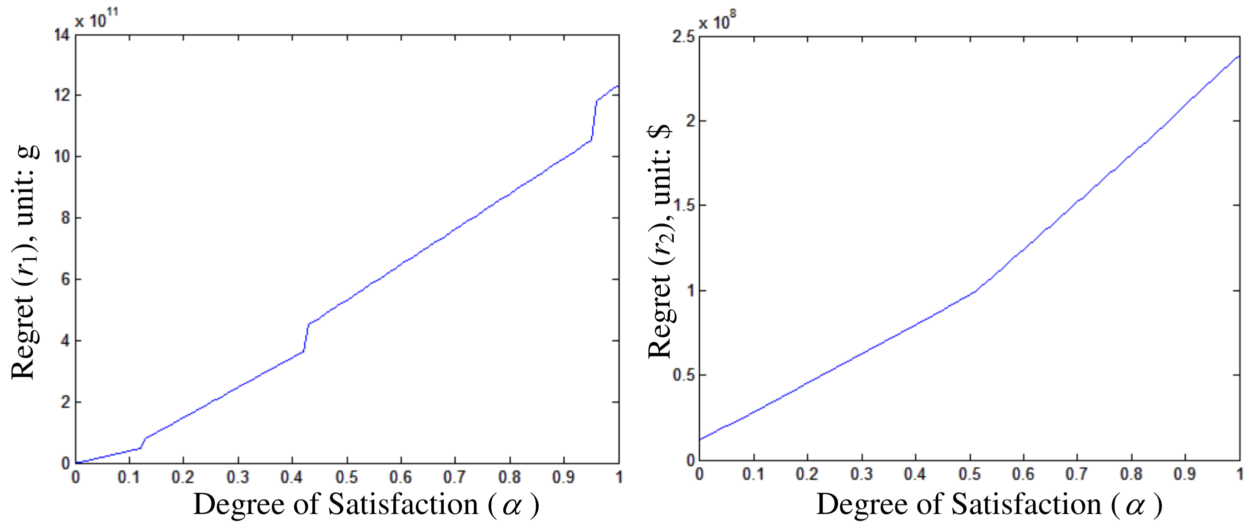


Figure 5-11 The first tier absolute regret of the two objectives

Table 5-10 Payoff table for the two minimax regret objectives

α =0.4	r_1	r_2	α =0.6	r_1	r_2	α =0.8	r_1	r_2
$\mathbf{X}(r_1)$	343.85	87.21	$\mathbf{X}(r_1)$	647.52	162.65	$\mathbf{X}(r_1)$	878.76	244.86
$\mathbf{X}(r_2)$	723.65	79.56	$\mathbf{X}(r_2)$	1244.8	124.19	$\mathbf{X}(r_2)$	1586.4	180.03

r1, unit: 109 g r2, unit: 106 $

For the NMMR solution, we again sweep the α value from 0 to 1 with step size 0.01 and find the NMMR solution by repetitional use of the NMMR solution method. The results are plotted in Figure 5-12. The vertical axis in Figure 5-12 represents the nested minimax regret which is also the compromised solution between the two conflicting objectives based on the criterion to minimizing the maximal relative regrets. The NMMR solutions in term of α are plotted together with the first tier absolution regrets of r_1 and r_2 in Figure 5-13.

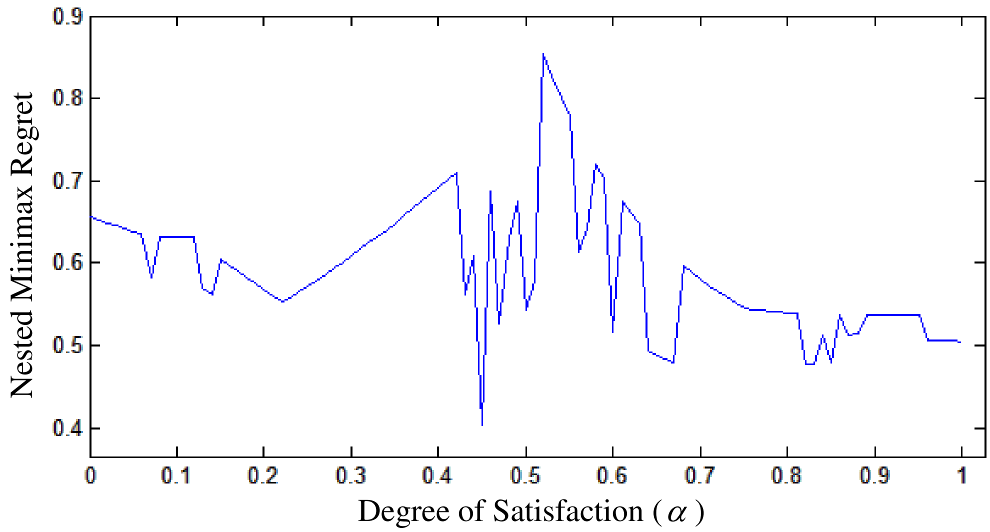


Figure 5-12 Nested minimax regret in term of degree of satisfaction

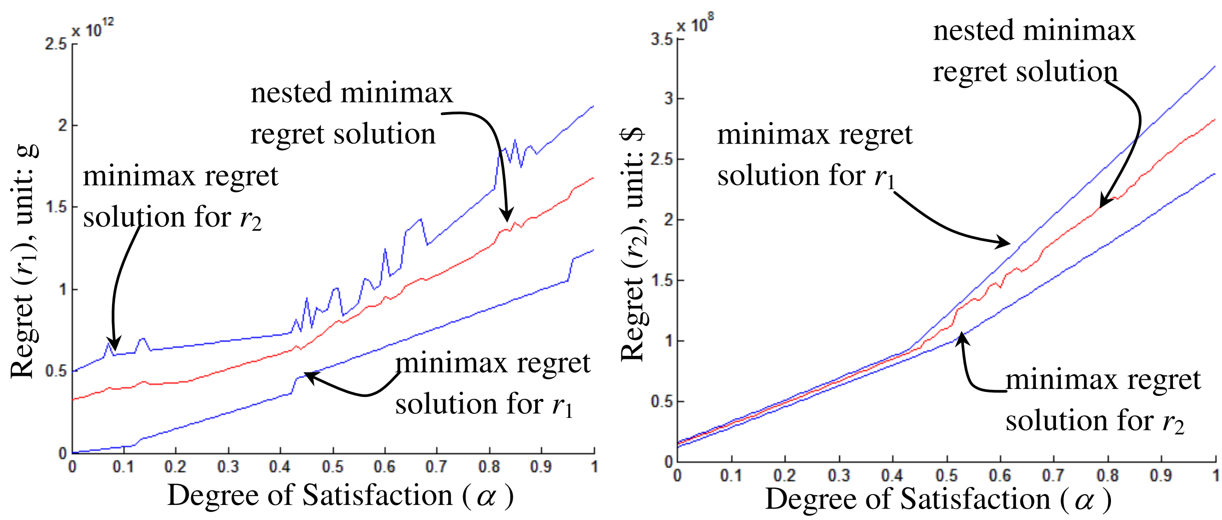


Figure 5-13 Nested minimax regret solutions v.s. minimax regret solutions

As a compromised solution, the NMMR output lies between the minimax regret solutions of the two first-tier regret objectives (Figure 5-13). The facility expansion strategies suggested by the NMMR solution method in case of $\alpha = 0.4, 0.6$ and 0.8 are listed in Table 5-11. Comparing with the facility expansion recommendations in Table 5-9, the NMMR solution harmonizes the two conflicting objectives, thereby being deemed more robust in response to the uncertainties. Under the assumption that decision makers require equal degree of satisfactions associated with all non-deterministic constraints, the NMMR solutions suggest that the options of water transfer is always preferred in all cases due to its relatively low carbon footprint burden and low unit cost within the system boundary. However, the underlying assumption of the low carbon footprint burden of water transfer options is that GHG emissions are negligible within the defined system boundary which is the Manatee County. When considering the global warming potential in a broader sense that is out of the defined system boundary, the water transfer options should be reconsidered. Groundwater option appears to be an irreplaceable option among the five options. Regional water and other options are only needed to offset the water demand when the supply of groundwater and transferred water options is not sufficient. Regional water option shows more cost efficient but not as environmentally friendly as other options due to its larger carbon footprints burden. The NMMR solution suggests that implementation of both regional water and other options would be a more robust solution than implementing only one of them especially when decision makers can tolerate a lower risk to violate the non-deterministic constraints. The surface water option shows no competitive strength among the five options. More studies on the global warming impacts and unit costs of surface water options may be needed to reduce the interval of uncertainties before it may be considered by decision making process under uncertainties via the NMMR approach. This result positively supports the research findings in Section 5.3.

Table 5-11 Nested minimax regret solution for facility expansion strategy

NMMR Solution	$\alpha = 0.4$	$\alpha = 0.6$	$\alpha = 0.8$
Ground Water Options	11.268	12.114	9.842
Surface Water Options	0	0	0
Transferred Water Options	17.03	17.03	17.03
Regional Water Options	1.404	3.31	6.126
Other Options	0	6.625	15.458

Unit: 1,000 m^3d^{-1}

CHAPTER SIX: CONCLUSION

This study conducted a thorough system analysis via a real-world drinking water infrastructure system expansion program in Manatee County, Florida. Four interrelated sub-systems of the drinking water infrastructure system were investigated and studied, which consisted of water demand analysis, global climate change evaluation, system optimization for infrastructure expansion and decisions under uncertainties.

In the water demand analysis, it was believed that system dynamics model carried unique features that would support the illustrative needs for complex interactions among system components for water demand estimation and forecasting. The case study using the system dynamics modeling tool to estimate the domestic water demand from 2003 to 2009 for Manatee Country, Florida was made successful even the historical data of population and water consumption were limited. Such a practice leaded to illuminate the modeling challenge - how do we build up a representative model to account for the interactions among those factors under global macroeconomic changes at different temporal scale in an urban region. The unemployment rate and average annual income were deemed as two principal indicators of the changing macroeconomic environments. With proper assumptions associated with these two driving forces, the system dynamics model could be used to estimate and forecast the future water demand under the impact of changing macroeconomic environments.

In the global climate change evaluation sub-system, carbon footprint analysis which quantifies the CO_2 equivalent emissions in every phase of the life cycle for each of the twenty expansion alternatives was performed. This result provided the chance of inclusion of GHG emissions as an extra dimension for decision makers in planning water infrastructure expansion strategies in Manatee County. A sensitivity analysis with the aid of Gabi® 4.0 education version was conducted and the most sensitive input parameters under uncertainties that may affect the system output the most were highlighted.

In the system optimization analysis, carbon footprint was included as an environmental objective in addition to the economic efficiencies when identifying the optimal water infrastructure expansion strategies subject to technical, managerial, and social constraints in Manatee County. Based on the trade-offs between costs and carbon footprints, the Pareto Optimal solution sets were identified using the distance-based metrics in a compromise programming model. Such a practice ended up generating some lucid suggestions after screening and sequencing these alternatives over four specified time periods.

To handle the potential uncertainties in the system optimization model, the NMMR solution method was proposed. The novel solution method was used to solve the multiobjective interval linear programming. A compromising and conservative solution was obtained by applying the NMMR solution method. The results reinforced the suggestions and recommendations to Manatee County decision makers for the strategies in planning the water infrastructure system expansion.

As a final remark, it is recommended from this research that MARS projects need to be implemented by 2015 for potential water demand increase by 2025. Starting from 2026, there will have a variety of optimal expansion strategies based on the decision maker’s preference. The groundwater options and water transfer options are always preferred because they are deemed environmentally benign and economically efficient simultaneously. However, the negligible carbon footprint associated with water transfer options in decision making are mainly due to our defined system boundary that is the Manatee County. When considering the global warming potential in the broader sense, decision makers may need to think more before the implementation of water transfer options. Needless to say that these type of water transfer options normally involve the complexity of political economy that may further compound the decision making arena. To reduce the risks associated with the uncertainties in water supply and demand data, estimated unit costs and global climate change impact of each water alternatives, both regional water and other options are recommended for a more robust and conservative strategy.

REFERENCES

Abbott, M.D., and Stanley, R.S., 1999. Modeling groundwater recharge and flow in a upland fracture bedrock aquifer. *System Dynamics Review*. 15, 163−184

Altunkaynak, A., Oezger, M., and Cakmakci, M., 2005. Water consumption prediction of Istanbul City by using fuzzy logic approach. *Water Resources Management*. 19, 641-654

Alvisi, S., Franchini, M., and Marinelli, A., 2007. A short-term, pattern-based model for water-demand forecasting. *Journal of Hydroinformatics*. 09.1, 39-50

Aly, A., and Wanakule, N., 2004. Short-Term Forecasting for Urban Water Consumption. *Journal of Water Resources Planning and Management*. 130(5), 405-410.

Athanasiadis, I.N., Mentes, A.K., Mitkas, P.A., and Mylopoulos, Y.A., 2005. A Hybrid Agent-Based Model for Estimating Residential Water Demand. *Simulation*. 81(3), 175-187

Babel, M.S., Gupta, A.D., and Pradhan, P., 2007. A multivariate econometric approach for domestic water demand modeling: An application to Kathmandu, Nepal. *Water Resources Management*. 21, 573-589.

Bagheri, A., and Hjorth, P., 2007. A framework for process indicators to monitor for sustainable development: practice to an urban water system. Environment, *Development and Sustainability*. 9(2), 143-161

Billings, R, and Agthe, D., 1998. State-Space Versus Multiple Regression for Forecasting Urban Water Demand. *Journal of Water Resources Planning and Management*. 124(2), 113–117

Birge, J.R., and Louveaus, F., 1997. *Introduction to Stochastic Programming*. Springer.

Bitran, G.R., 1980. Linear Multiple Objective Problems with Interval Coefficients. *Management Science*. 26(7), 694-706

Bjoerklund, A.E., 2002. Survey of approaches to improve reliability in LCA. *International Journal of Life Cycle Assessment*. 7(2), 64-72

Bougadis, J., Adamowski, K., and Diduch, R. 2005. Short-term Municipal Water Demand Forecasting. *Hydrological Processes*. 19, 137-148

Bradley, S.P., Hax, A.C., and Magnanti, T.L., 1977. *Applied Mathematical Programming*. Addison-Wesley: Reading, Massachusetts.

Burnley, I., Murphy, P., and Fagan, R. 1997. *Immigration and Australian Cities*, The Federation Press, Sidney.

Caiado, J., 2007. Forecasting water consumption in Spain using univariate time series models. Published in: *Proceedings of IEEE Spanish Computational Intelligence Society*, September 2007, 415-423

Case, K.E., 1991. The real estate cycle and the economy: consequences of the Massachusetts boom of 1984-1987. *New England Economic Review* (September-October). 37-46

Case, K.E., Glaeser, E.L., and Parker, J.A., 2000. Real estate and the macroeconomy. *Brookings Papers on Economic Activity*. 2, 119-162

Cerci, Y., Cengel, Y.A., and Wood, B., 1999. Minimum separation work for desalination processes. *ASME Advanced Energy Systems Division AES*. 39, 545-552

Chanas, S., and Kuchta, D., 1996. Multiobjective programming in optimization of interval objective functions – a generalized approach. *European Journal of Operational Research*. 94, 594-598

Chang, N.B., Chen, Y.L., and Wang, S.F., 1997. A fuzzy interval multiobjective mixed integer programming approach for the optimal planning of solid waste management systems. *Fuzzy Sets and Systems*. 89, 35-60

Chang, N.B., and Davila, E., 2007. Minimax regret optimization analysis for a regional solid waste management system. *Water Management*. 27, 820-832

Cao, M.F., Huang, G.H., and Lin, Q.G., 2010. Integer programming with random-boundary intervals for planning municipal power systems, *Applied Energy*. 87(8), 2506-2516

Cheng, G.H., Huang, G.H., Li, Y.P., Cao, M.F., and Fan, Y.R., 2009. Planning of municipal solid waste management systems under dual uncertainties: a hybrid interval stochastic programming approach, *Stochastic Environmental Research and Risk Assessment*. 23(6), 707-720

Chinneck, J.W., and Ramadan, K., 2000. Linear programming with interval coefficients. *Journal of Operation Research Society*. 51, 209-22

Cole, R.J., 1998. Energy and greenhouse gas emissions associated with the construction of alternative structural systems. *Building and Environment*. 34(3), 335-348

Cole, R.J., 2000. Building environmental assessment methods: assessing construction practices. *Construction Management and Economics*. 18(8), 949-957

Conlisk, J., 1971. A Bit of Evidence on the Income-Education-Ability Interrelation. *The Journal of Human Resources*. 6(3), 358-362

Coxson, G.E., 1999. Computing exact bounds on elements of an inverse interval matrix is NP-hard, *Reliable Computing*, 5(2), 137-142

Cutore, P., Campisano, A., Kapelan, Z., Modica, C., and Savic, D. 2008. Probabilistic prediction of urban water consumption using the SCEM-UA algorithm, *Urban Water Journal*. 5(2), 125-132

Davis, W.Y., 2003. Water Demand Forecast Methodology for California Water Planning Areas - Work Plan and Model Review. *Research Report*, California Bay-Delta Authority, CA, USA.

Deaton, M.L., and Winebrake, J.J., 2000. *Dynamic Modeling of Environmental Systems*. Springer-Verlag, New York, USA.

Dennison, F.J., Azapagic, A., Clift, R., and Colbourne, J. S., 1998. Assessing management options for wastewater treatment works in the context of life cycle assessment. *Water Science and Technology*. 38(11), 23–30

Dyson, B., and Chang, N.B., 2005. Forecasting of solid waste generation in an urban region by system dynamics modeling, *Waste Management*, 25(7), 669-679

Finnveden, G., 2000. On the limitations of life cycle assessment and environmental systems analysis tools in general. *International Journal of Life Cycle Assessment*. 5 (4), 229-238

Florida Department of Environmental Protection, 2010. <http://www.floridadep.org/air/emission/construction.htm, Retrieved 01.30.2010>

Ford, A., 1999. *Modeling the Environment*. Island Press, Washington, DC, USA.

Forrester, J.W., 1961. *Industrial Dynamics*. The MIT Press, Cambridge, Massachusetts, USA

Forrester, J.W., 1968. *Principles of System*. Cambridge, Massachusetts, Productivity Press, MA

Forrester, J.W., 1969. *Urban Dynamics*. Cambridge, The MIT Press, MA, USA.

Foster, H.S., and Beattie, B.R., 1979. Urban Residential Demand for Water in the United States. *Land Economics*. 55(1), 43-58

Franklin, S.L., and Maidment, D.R., 1986. An evaluation of weekly and monthly time series forecasts of municipal water use, *Journal of American Water Resources Association*. 22(4), 611–621

Friedrich, E., 2001. The use of environmental life cycle assessment for the production of potable water. *MSc Eng Thesis*. Pollution Research Group, University of Natal: Durban; 2001.

Friedrich, E., 2002. Life cycle assessment as an environmental management tool in the production of potable water. *Water Science and Technology*. 46(9), 29-36

Friedrich, E., Pillay, S., and Buckley, C.A., 2009. Carbon footprint analysis for increasing water supply and sanitation in South Africa: a case study. *Journal of Cleaner Production*. 17, 1-12

Fronstin P., 1998. Sources of health insurance and characteristics of the uninsured: analysis of the March 1998 Current Population Survey. Washington, D.C.: Employee Benefit Research Institute, December 1998. (Issue brief no.204.)

Fullerton, T.M., Jr., and Elias A., 2004. Short-term water consumption dynamics in El Paso, Texas. *Water Resources Research*. 40, W08201, doi:10.1029/2004WR003260

Gato, S., Jayasuriya, N., and Roberts, P., 2007. Temperature and rainfall thresholds for base use urban water demand modeling. *Journal of Hydrology*. 337, 364-376

Ghiassi, M., Zimbra, D.K., and Saidane, H., 2008. Urban water demand forecasting with a dynamic artificial neural network model. *Journal of Water Resources Planning and Management*. 134(2), 138-146

Grant, W.E., Pedersen, E.K., and Marin, S.L., 1997. *Ecology and Natural Resource Management: Systems Analysis and Simulation*. Wiley, New York, USA.

Guo, H.C., Liu, L., Huang, G.H., Fuller, G.A., Zou, R., and Yin, Y.Y., 2001. A system dynamics approach for regional environmental planning and management: a study for Lake Erhai Basin. *Journal of Environmental Management*. 61, 93−111

Hancock, D., and Wilcox, J.A., 1997. Bank capital, nonbank finance, and real estate activity. *Journal of Housing Research*, 8(1), 75-105

Hansen, R.D. and Narayanan, R., 1981, A monthly time series model of municipal water demand. *Journal of American Water Resources Association*. 17(4), 578-585

Hardi, P., Berg, S., and Hodge, T., 1997. *Measuring sustainable development: a review of current practice*. International Institute for Sustainable Development, Winnipeg, Manitoba, Canada

Harger, J.R.E., and Meyer, F.M., 1996. Definition of indicators for environmentally sustainable development. *Chemosphere*. 33, 1749–1775

Hellström, D., Jeppsson, U., and Kärrman, E., 2000. A framework for systems analysis of sustainable urban water management. *Environmental Impact Assessment Review*. 20, 311–321

Hodge, T., 1997. Toward a conceptual framework for assessing progress towards sustainability. *Social Indicators Research*. 40(1–2), 5–98

Homwongs, C., Sastri, T., and Foster, J. W., III., 1994. Adaptive forecasting of hourly municipal water consumption. *Journal of Water Resources Planning and Management*. 120(6), 888–905

Hospido, A., Moreira, M.A., and Feijoo, G., 2008. A comparison of municipal wastewater treatment plants for big centres of population in Galicia (Spain). *International Journal of Life Cycle Assessment*. 13(1), 57-64

Howe, C.W., and Linaweaver, F.P., 1967. The Impact of Price on Residential Water Demand and Its Relation to Systems Design. *Water Resources Research*. 3(1), 13–22

Huang, G.H., Baetz, B.W., and Patry, G.G., 1992. A grey linear programming approach for municipal solid waste management planning under uncertainty. *Civil Engineering Systems*. 9, 319-335

Huang, G.H., 1994. Grey mathematical programming and its application to municipal solid waste management planning, *PhD Dissertation*, Department of Civil Engineering, McMaster University, Ont, Canada

Huang, G.H., Sae-Lim, N., Liu, L., and Chen, Z., 2001. An interval-parameter fuzzy-stochastic programming approach for municipal solid waste management and planning. *Environmental Modeling and Assessment*. 6(4), 271-283

Huang, G.H. and Cao, M.F., 2011. Analysis of solution methods for interval linear programming. *Journal of Environmental Informatics*. 17(2), 54-64

Hughes, T.C., 1980. Peak period design standards for small western U.S. water supply system. *Journal of the American Water Resources Association*. 16(4), 661-667

Ida, M., 2005. Efficient solution generation for multiple objective linear programming based on extreme ray generation method. *European Journal of Operational Research.* 160, 242-251

Inuiguchi, M., Ichihashi, H., and Tanaka, H., 1990. Fuzzy programming: a survey of recent developments, in: Slowinski, R. and Teghem, J. (Eds.), *Stochastic Versus Fuzzy Approaches to Multiobjective Programming under Uncertainty*, Kluwer Academic Publishers, Dordrecht, 45-68

Inuiguchi, M., and Sakawa, M., 1995. Minimax regret solution to linear programming problems with an interval objective function. *European Journal of Operational Research.* 86, 526-536

Inuiguchi, M., and Sakawa, M., 1996. Possible and necessary efficiency in possibilistic multiobjective linear programming problems and possible efficiency test. *Fuzzy Sets and Systems*. 78, 231-241

Inuiguchi, M., and Ramik, J., 2000. Possibilistic linear programming: a brief review of fuzzy mathematical programming and a comparison with stochastic programming in portfolio selection problem, *Fuzzy Sets and* Systems. 111, 3-28

Ishihuchi, H., and Tanaka, M., 1990. Multiobjective programming in optimization of the interval objective function. *European Journal of Operational Research*. 48, 219-225

ISO 14040, 2006. *Environmental management—life cycle assessment—principles and framework*. International Organization for Standardization, Geneva, Switzerland

ISO 14043, 2000. Environmental Management - Life Cycle assessment - Life Cycle Interpretation. ISO 14043

Jain, A., Vershney, A.K., and Joshi, U.C., 2001. Short-term water demand forecast modeling at IIT Kanpur using artificial neural networks. *Water Resources Management*. 15, 299-321

Jain, A., and Kumar, A.M., 2006. Hybrid neural network models for hydrologic time series forecasting. *Applied Soft Computing*. 7(2), 585-592

Jamison, K.D., and Lodwick, W.A., 2001. Fuzzy linear programming using a penalty method. *Fuzzy Sets and Systems*. 119, 97-110

Jowitt, P.W., and Xu, C., 1992. Demand Forecasting for Water Distribution Systems, *Civil Engineering System*. 9, 105–121

Kall, P., and Wallace, S.W., 1994. *Stochastic programming*. John Wiley and Sons Ltd, Chichester. ISBN 9780471951087

Karavezyris, V., Timpe, K., and Marzi, R., 2002. Application of system ynamics and fuzzy logic to forecasting of municipal solid waste. *Mathematics and Computers in Simulation*. 60(3-5), 149−158

Khatri, K.B., and Vairavamoorthy, K., 2009. Water demand forecasting for the city of the future against the uncertainties and the global change pressures: case of Birmingham. *EWRI/ASCE*. Conference at Kansas, USA. May 17-21, 2009.

Kravdal, O., 1992. The Emergence of a Positive Relation Between Education and Third Birth Rates in Norway with Supportive Evidence from the United State. *Population Studies*. 46, 459-475

Kuchta, D., 2008. A modification of a solution concept of the linear programming problem with interval coefficients in the constraints. *Central European Journal of Operational Research*. 16, 307-316

Kutter, R., 1999. The American health care system: employer-sponsored health coverage, Health Policy Report. *The New England Journal of Medicine*, January 21, 1999, 248-252

Lai, Y.J., and Hwang, C.L., 1993. Possibilistic linear programming for managing interest rate risk. *Fuzzy Sets and Systems*. 54, 135-146

Lenzen, M., 2008. Life cycle energy and greenhouse gas emissions of nuclear energy: A review. *Energy Conversion and Management*. 49, 2178-2199

Li , Y.P., and Huang, G.H., 2006. Minimax regret analysis for municipal solid waste management: an interval-stochastic programming approach. *Journal of the Air & Waste Management Association*. 56(7), 931-944

Li, Y. P., Huang, G. H., Chen, X., and Cheng, S. Y., 2009. Interval-parameter robust minimax-regret programming and its application to energy and environmental systems planning. *Energy Sources, Part B: Economics, Planning, and Policy*, 4(3), 278-294

Liu, B., and Iwamura, K., 1998. Chance constrained programming with fuzzy parameters. *Fuzzy Sets and Systems*. 94(2), 227-237

Liu, J., Savenije, H.H.G., and Xu, J., 2003. Forecast of water demand in Weinan City in China using WDF-ANN model. *Physics and Chemistry of the Earth*. 28, 219-224

Lodwick, W.A., and Jamison, K.D., 2007. Theoretical and semantic distinctions of fuzzy, possibilistic, and mixed fuzzy/possibilistic optimization. *Fuzzy Sets and Systems*. 158, 1861-1872

Lundie, S., Peters, G.M., and Beavis, P.C., 2004. Life cycle assessment for sustainable metropolitan water systems planning, *Environmental Science and Technology*. 38, 3465-3473

Lundin, M., Bengtsson, M., and Molander, S., 2000. Life cycle assessment of wastewater systems: influence of system boundaries and scale on calculated environmental loads. *Environmental Science and Technology*. 34, 180–186

Lundin, M., and Morrison, G.M., 2002, A life cycle assessment based procedure for development of environmental sustainability indicator of urban water systems. *Urban Water*. 4(2), 145-152

Luo, B., Maqsood, I., Yin, Y.Y., Huang, G.H., and Cohen, S.J., 2003. Adaption to climate change through water trading under uncertainty-An inexact two-stage nonlinear programming approach. *Journal of Environmental Informatics*. 2, 58–68

Maidment, D.R., Miaou, S.P., and Crawford, M.M., 1985. Transfer function models of daily urban water use. *Water Resources Research*. 21(4), 425-432

Maidment, D.R., Miaou, S.P., and Crawford, M.M., 1986. Daily water use in nine cities. *Water Resources Research*. 22(6), 845-851

Maidment, D. R., and Parzen, E.: 1984b, Time Patterns of Water Use in Six Texas Cities, *Journal of Water Resources Planning and Management*. 110(1), 90–106

Maqsood, I., Huang, G.H., and Yeomans, J.S., 2005. An interval-parameter fuzzy two-stage stochastic program for water resources management under uncertainty. *European Journal of Operational Research*. 167(1), 208-255

Martinson, F.K., 1993. Fuzzy vs. minmax weighted multiobjective linear programming illustrative comparisons. *Decision Sciences*. 24(4), 809-824

Mashayekhi, A.N., 1993. Transition in New York State solid waste system: a dynamic analysis. *System Dynamics Review*. 9, 23−48

Mausser, H.E., and Laguna, M., 1999. A heuristic to minimax absolute regret for linear programs with interval objective function coefficients. *European Journal of Operational Research*. 117, 157-174

Meadows, D.L., and Meadows, D.H. (Eds.), 1973. *Toward Global Equilibrium*. Collected Papers. Wright-Allen Press, MA, USA.

Miaou, S.P., 1990. A class of time series urban water demand models with nonlinear climatic effects. *Water Resources Research*. 26(2), 169-178

Mohapatra, P.K., 1994. *Introduction to System Dynamics Modeling*. Orient Longman Ltd, New York, USA.

Molino, B., Rasulo, G., and Taglialatela, L., 1996. Forecast model of water consumption for Naples. *Water Resources Management*. 10(4), 321-332

Mráz, F., 1998. Calculating the exact bounds of optimal values in LP with interval coefficients. *Annals of Operations Research*. 84, 51-62

Msiza, I.S., Nelwamondo, F.V., and Marwala, T., 2007. Water demand forecasting using multi-layer perceptron and radial basis functions. *Proceedings of International Joint Conference on Neural Networks*, Orlando, Florida, USA, August 12-17, 2007.

Nail, R.F., Gelanger, S., Klinger, A., and Peterson, E., 1992. An analysis of cost effectiveness of US energy policies to mitigate global warming. *System Dynamics Review*. 8, 111−118

Nefti, S., 1984. Are economic time series asymmetric over the business cycle?. *Journal of Political Economy*. 92, 307-328

Nie, X.H., Huang, G.H., Li, Y.P., and Liu, L., 2007. IFRP: A hybrid interval-parameter fuzzy robust programming approach for waste management planning under uncertainty. *Journal of Environmental Management*. 84(1), 1-11

Oliveira, C., and Antunes, C.H., 2007. Multiple objective linear programming models with interval coefficients – an illustrated overview. *European Journal of Operational Research*. 181, 1434-1463

Pannell, D.J., and Glenn, N.A., 2000. A framework for the economic evaluation and selection of sustainability indicators in agriculture. *Ecological Economics*. 33, 135–149

Parkin, D., McGuire, A., and Yule, B., 1987. Aggregate health care expenditures and national income. Is health care a luxury good? *Journal of Health Economics*. 6(2), 109-27

Parkinson, J., and Butler, D., 1998. *Developing a methodology to measure the sustainability of urban wastewater systems. The myth of cycles versus sustainable water and material flux management*. In 11th Junior workshop, Wildpark Eekholt, Germany

Pasqualino, J.C., Meneses, M., and Castells, F., 2011. Life cycle assessment of urban wastewater reclamation and reuse alternatives. *Journal of Industrial Ecology*. 15(1), 49-63

PE International, 2009. Gabi Software <http://www.gabi-software.com/, Retrieved 2009>

Peisajovich, A., Chamberland, A., and Gagnon, L., 1996. Greenhouse gases from full energy cycle of northern hydro-electricity (preliminary assessment of production and transportation). In: Assessment of Greenhouses Gas Emissions from the Full Energy Chain for Hydropower, Nuclear Power and Other Energy Sources. Papers Presented at an IAEA Advisory Group Meeting Jointly Organized by Hydro-Quebec and the International Atomic Energy Agency, Hydro-Quebec Headquarters, Montreal, Canada

Peters, G. M., and Lundie, S., 2001. Life-cycle assessment of biosolids processing options. *Journal of Industrial Ecology*. 5(2), 1088-1980

Pillay, S.D., 2005. An environmental life cycle assessment of the provision of recycled water in Durban. *PhD Thesis*. Pollution Research Group. University of KwaZulu-Natal: Durban, South Africa

Pulido-Calvo, I., and Gutierrez-Estrada, J.C., 2007. Improved irrigation water demand forecasting using a soft-computing hybrid model. *Biosystems Engineering*. 102(2), 202-218

Qu, W., and Barney, G.O., 1998. *Projecting China's Grain Supply and Demand Using a New Computer Simulation Model*. Millennium Institute, Arlington, VA.

Randers, J. (Ed.), 1980. *Elements of the System Dynamics Method*. Cambridge, Productivity Press, MA

Richardson, G.P., Pugh III, A.L., 1981. *Introduction to System Dynamics Modeling with DYNAMO*. Cambridge, Productivity Press, MA.

Rommelfanger, H., Hanuscheck, R., and Wolf, J., 1989. Linear programming with fuzzy objectives. *Fuzzy Sets and Systems*. 29, 31-48

Rothman, P., 1991. Further evidence on the asymmetric behavior of unemployment rates over the business cycle. *Journal of Macroeconomics*. 13, 291-298

Ruszczyński, A., and Shapiro, A., 2003. Stochastic programming. *Handbooks in Operations Research and Management Science*. 10, 1-64

Saiz, A., 2003. Room in the kitchen for the melting pot: Immigration and rental prices, *Review of Economics and Statistics*, 85, 502-521

Saiz, A., 2007. Immigration and housing rents in American cities, *Journal of Urban Economics*. 61, 345-371

Sastri, T., and Valdes, J.B., 1989. Rainfall intervention analysis for on-line applications. *Journal of Water Resoucres Planning and Management*. 115(4), 397-415

Savenije, H., and van der Zaag, P., 2002. Water as an economic good and demand management paradigms with pitfalls. *International Water Resources Association*. 27(1), 98-104

Saysel, A.K., Barlas, Y., and Yenigun, O., 2002. Environmental sustainability in an agricultural development project: a system dynamics approach. *Journal Environmental Management*. 64, 247−260

Sengupta, A, Pal, T.K., and Chakraborty, D., 2001. Interpretation of inequality constraints involving interval coefficients and a solution to interval linear programming. *Fuzzy Sets and Systems*. 119, 129-138

Sichel, D., 1989. Three essays in business cycle asymmetry. Unpublished *Ph.D thesis*, Princeton university, Department of Economics.

Shimizu, K., and Aiyoshi, E., 1980. Necessary conditions for min-max problems and algorithms by a relaxation procedure, *IEEE Transactions on Automatic Control*. 25, 62-66

Shvartser L., Shamir, U., and Feldman, M., 1993. Forecasting hourly water demands by pattern recognition approach. *Journal of Water Resources Planning and Management*. 119(6), 611-627

Smith, C.S., amd MacDonald, G.M., 1998. Assessing the sustainability of agriculture at the planning stage. *Journal of Environmental Management*. 52, 15–37

Smith, J.A., 1988, A model of daily municipal water use for short-term forecasting. *Water Resources Research*. 24(2), 201-206

Solomatine, D.P., and Xue, Y., 2004. M5 model trees and neural networks: application to flood forecasting in the upper reach of the Huai River in China. *Journal of Hydrologic Engineering*. 9(6), 491-501

Stella®, High Performance System, Inc., USA. Available from: <http://www.hps-inc.com/stellavpsr.htm>

Sterman, J.D., 2000. *Business Dynamics: Systems Thinking and Modeling for a Complex World*. McGraw-Hill, Irwin, USA.

Steuer, R.E., 1986. *Multiple Criteria Optimization: Theory, Computation and Application*. John Wiley & Sons, New York

Stokes, J., and Horvath, A., 2006. Life cycle energy assessment of alternative water supply systems. *The International Journal of Life Cycle Assessment*. 11(5), 335-343

Stokes, J., and Horvath, A., 2009. Energy and air emission effects of water supply. *Environmental Science and Technology*. 43(8), 2680-2687

Strutt, J., Wilson, S., Shorney-Darby, H., Shaw, A., and Byers, A., 2008. Assessing the carbon footprint of water production. *American Water Works Association*. 100(6), 80-91

Stubbles, J., 2000. Energy use in the U.S. steel industry: an historical perspective and future opportunities. Prepared for the U.S. Department of Energy, Office of Industrial Technologies, Washington, DC, USA

Struble, L., and Godfrey, J., 2004. How sustainable is concrete? *Proceedings of the International Workshop on Sustainable Development and Concrete Technology*, Beijing, 201-211.

Sudhir, V., Srinivasan, G., and Muraleedharan, V.R., 1997. Planning for sustainable solid waste in Urban India. *System Dynamics Review*. 13, 223−246.

System Dynamics Society/System Dynamics Review. Available from: <http://www.albany.edu/cpr/sds/>

Tillman, A. M., Lundertroem, H., and Svingby, M., 1998. Life cycle assessment of municipal waste water systems. *International Journal of Life Cycle Assessment*. 3, 145–157

Tong, S.C., 1994. Interval number and fuzzy number linear programmings. *Fuzzy Sets and Systems*. 66, 301-306

Urli, B., and Nadeau, R., 1992. An interactive method to multiobjective linear programming problems with interval coefficients. *Information Systems and Operational Research*. 30(2), 127-137

United States Environmental Protection Agency., 1995. Guidelines for Assessing the Quality of Life CycleInventory Analysis. Office of Solid Waste, US Environmental Protection Agency, Washington, DC, USA

Vensim®, Ventana System, Inc. Available from: <http://www.vensim.com>

Vezjak, M., Savsek, T., and Stuhler, E.A., 1998. System dynamics of euthrophication processes in lakes. *European Journal of Operational Research*. 109, 442–451

Vince, F., Aoustin, E., Bréant, P., and Marechal, F., 2007. LCA tool for the environmental evaluation of potable water production. *Desalination*. 220(1-3), 37-56

Vizayakumar, K., and Mohapatra, P.K.J., 1991. Environmental impact analysis of a coalfield. *Journal of Environmental Management*. 34, 73−93

Vizayakumar, K., and Mohapatra, P.K.J., 1993. Modeling and simulation of environmental impacts of a coalfield: system dynamic approach. *Journal of Environmental Management*. 42, 59−73

Walski, T., Whitman, B., Baron, and M., Gerloff, F., 2009. Pressure vs. flow relationship for pipe leaks. World Environmental and Water Resources Congress 2009: Great Rivers Proceedings of World Environmental and Water Resources Congress, ASCE

Wang, H.F. and Wang, M.L., 2001. Decision analysis of the interval-valued multiobjective linear programming problems.

Weisser, D., 2007. A guide to life-cycle greenhouse gas (GHG) emissions from electric supply technologies. *Energy*. 32(9), 1543-1559

Wennberg, J.E, Roos, N, Sola, L, Schori, A., and Jaffe, R., 1987. Use of Claims Data Systems to Evaluate Health Care Outcomes, *The Journal of the American Medical Association*. 257, 933-936

Wood, T.S., and Shelley, M.L., 1999. A dynamic model of bioavailability of metals in constructed wetland sediments. *Ecological Engineering*. 12, 231−252

Wu, L., and Zhou, H., 2009. Urban water demand forecasting based on HP filter and fuzzy neural network. *Journal of Hydroinformatics*. 12(2), 172-184

Yurdusev, M.A., Firat, M., Mermer, M., and Turan, M.E., 2009. Water use prediction by radial and feed-forward neural nets. *Water Management*. 162(3), 179-188

Zeleny, M., 1973. *Compromise programming, in: Multiple Criteria Decision Making*, eds: J. L. Cochrane and M. Zeleny, University of South Carolina Press, Columbia, SC, pp. 262-301.

Zhou, S.L., McMahon, T.A., Walton, A., and Lewis, J., 2000. Forecasting daily urban water demand: a case study of Melbourne. *Journal of Hydrology*. 236, 153-164

Zhou, S.L., McMahon, T.A., Walton, A., and Lewis, J., 2002. Forecasting operational demand for an urban water supply zone. *Journal of Hydrology*. 259,189-202

Zimmermann, H.J., 1978. Fuzzy programming and linear programming with several objective function. *Fuzzy Sets and Systems*. 1(1), 45-55