INCORPORATING ENVIRONMENTAL IMPACTS INTO MULTI-OBJECTIVE OPTIMIZATION OF WATER DISTRIBUTION SYSTEMS

by

Lesley Maureen Herstein

A thesis submitted to the Department of Civil Engineering

In conformity with the requirements for

the degree of Master of Science (Engineering)

Queen’s University

Kingston, Ontario, Canada

(August, 2009)

Copyright ©Lesley Maureen Herstein, 2009
Abstract

Municipal water distribution system (WDS) expansion is often focused on increasing system capacity with designs that best meet hydraulic requirements at the least cost. Increasing public awareness regarding global warming and environmental degradation is making environmental impact an important factor in decision-making for municipalities. There is thus a growing need to consider environmental impacts alongside cost and hydraulic requirements in the expansion and design of WDSs. As a result, the multiplicity of environmental impacts to consider in WDS expansion can complicate the decisions faced by water utilities. For example, a water utility may wish to consider environmental policy issues such as greenhouse gas emissions, non-renewable resource use, and releases to land, water, and air in WDS expansion planning.

This thesis outlines a multi-objective optimization approach for WDS design and expansion that balances the objectives of capital cost, annual pumping energy use, and environmental impact minimization, while meeting hydraulic constraints. An environmental impact index that aggregates multiple environmental measures was incorporated as an environmental impact objective function in the multi-objective non-dominated sorting genetic algorithm-II (NSGA-II) optimization algorithm. The environmental impact index was developed to reflect stakeholder prioritization of specific environmental policy issues. The evaluation of the environmental impact index and its application to the WDS expansion problem was demonstrated with a water transmission system example. The environmental impact index and multi-objective non-dominated sorting genetic algorithm-II (NSGA-II) optimization algorithm were applied to the “Anytown” network expansion problem. Preliminary results suggest that solutions obtained with the triple-objective capital cost/energy/EI index optimization minimize a number of environmental impact measures while producing results that are comparable in pumping energy use and, in some instances, slightly higher in capital cost when compared to solutions obtained with a double cost/energy optimization in which environmental impact was not considered.
Acknowledgements

The completion of this thesis would not have been possible without the support and encouragement of a number of individuals. To begin with, I would like to acknowledge my graduate supervisors, Dr. Kevin Hall and Dr. Yves Filion. I believe that I have been fortunate enough to experience a truly unique situation in which both of my graduate supervisors went well beyond the traditional supervisory role in the completion of my thesis and ensured that my time at Queen’s was also an opportunity to develop professionally. They were completely invested in me and my development as a researcher, engineer, and teacher. Dr. Hall was instrumental in providing me with countless opportunities to participate in curriculum development, hone my teaching skills, and develop ideas regarding the non-technical aspects of engineering. I am particularly indebted to Dr. Filion for his endless devotion throughout my graduate studies at Queen’s. Dr. Filion gave me the freedom to explore new ideas and then spent a great deal of time and effort to ensure that my ideas were developed to their full potential. He has very generously provided me with an invaluable set of tools for the successful continuation of my academic career and for that I cannot thank him enough.

During the course of my masters program, I have had the great pleasure of interacting with the insightful, kind, and helpful graduate students of the Civil Engineering Department at Queen’s. I have learned so much from this diverse group of students and I would like to thank them for enriching my daily life at Queen’s.

Last, but certainly not least, I would like to thank my family for their everlasting support of my professional and personal decisions.
# Table of Contents

Abstract................................................................................................................................. ii
Acknowledgements.............................................................................................................. iii
Table of Contents ................................................................................................................ iv
List of Figures ........................................................................................................................ vii
List of Tables ........................................................................................................................ ix

Chapter 1: Introduction ........................................................................................................ 1
  1.1 Introduction ...................................................................................................................... 1
  1.2 Thesis objectives ............................................................................................................. 6
  1.3 Original Thesis Contributions ....................................................................................... 6
  1.4 Thesis Organization ....................................................................................................... 6
  1.5 Journal and Conference Publications Related to the Thesis ........................................ 8
  1.6 References ....................................................................................................................... 8

Chapter 2: Literature Review: Multi-Objective Genetic Algorithms and the NSGA-II in WDS Expansion ........................................................................................................ 11
  2.1 Introduction ...................................................................................................................... 11
  2.2 Overview of Enumeration, Linear Programming, Steepest Descent, and Stochastic Search Techniques in Single Objective Optimization .................................................. 11
  2.3 Overview of Genetic Algorithms in Single-Objective Optimization ............................... 13
  2.4 Multi-Objective Genetic Algorithms: Problem Definition .............................................. 14
  2.5 Multi-Objective Genetic Algorithms in WDS Design Optimization Research .............. 17
  2.6 Overview of the Non-Dominated Sorting Genetic Algorithm (NSGA-II) ......................... 18
    2.6.1 Initial population ......................................................................................................... 19
    2.6.2 Non-dominated sorting of the initial population ......................................................... 19
    2.6.3 Post-sorting population ............................................................................................. 21
    2.6.4 Selection, Crossover, Mutation ............................................................................... 21
    2.6.5 Recombination and reevaluation ............................................................................. 25
    2.6.6 Constraint handling ................................................................................................. 26
  2.7 Application of the NSGA-II in WDS Design Research ................................................... 26
  2.8 Summary ......................................................................................................................... 27
  2.9 References ....................................................................................................................... 27
Chapter 3: Developing and Applying an Environmental Impact Index for the Design and Expansion of Water Distribution Systems

3.1 Abstract ................................................................................................................................. 32
3.2 Introduction ............................................................................................................................ 33
3.3 Criteria for the Environmental Assessment of Water Networks ......................................... 34
   3.3.1 Complete Life Cycle Assessment ................................................................................. 34
   3.3.2 Functional Unit and Comparison of Alternatives ......................................................... 35
   3.3.3 Aggregation of Environmental Measures into a Single Index .................................... 35
   3.3.4 Environmental Releases and Ecological Degradation .................................................. 36
3.4 Environmental Impact Index ................................................................................................. 36
   3.4.1 Computing the Environmental Impact Index ................................................................. 38
3.5 Environmental Impact Index in Multi-Objective Optimization ............................................ 42
3.6 Case Study ............................................................................................................................. 44
   3.6.1 Functional Unit – Volume of Water Delivered ............................................................... 45
   3.6.2 Pipe Costs and Impacts ................................................................................................. 46
   3.6.3 Pumping Costs and Impacts ........................................................................................ 46
   3.6.4 Total Cost, Total Impacts, and Environmental Impact Index ....................................... 49
   3.6.5 Minimum Pressure Head .............................................................................................. 49
   3.6.6 Results ........................................................................................................................... 51
3.7 Broader Implications ............................................................................................................. 56
3.8 Summary and Conclusions ................................................................................................... 57
3.9 References ............................................................................................................................ 58

Chapter 4: Evaluating the Environmental Impacts of Water Distribution Systems Using EIO-LCA-Based Multi-Objective Optimization ......................................................... 60

4.1 Abstract ................................................................................................................................. 60
   4.1.1 Introduction .................................................................................................................... 61
4.2 Environmental Impact Index ................................................................................................. 62
   4.2.1 Environmental Categories and Environmental Measures ............................................ 62
   4.2.2 Step 1 – Evaluate Measure Indices for Each Individual ................................................. 64
   4.2.3 Step 2 – Average measure indices by category ............................................................... 64
   4.2.4 Step 3 – Evaluate EI Index ............................................................................................. 65
4.3 Network Expansion Formulation .......................................................................................... 65
   4.3.1 EIO-LCA-Based Multi-Objective Optimization Approach ........................................... 66
4.4 Non-Dominated Sorting Genetic Algorithm-II (NSGA-II) .............................................. 67
4.5 Anytown Case Study ........................................................................................................... 69
   4.5.1 Tank Location, Pipe Material, and Environmental Impacts ........................................... 70
   4.5.2 Chromosome Coding Structure ..................................................................................... 71
   4.5.3 Pipe Costs and Embodied Environmental Impacts of Pipe ........................................... 71
   4.5.4 Pipe Cleaning Costs ........................................................................................................ 72
   4.5.5 Tank Costs and Embodied Environmental Impacts of Tanks .......................................... 73
   4.5.6 Normal-Day Diurnal Demand, Energy Use, and Environmental Impacts of Pumping
   ............................................................................................................................................. 73
   4.5.7 Total Cost, Total Environmental Impacts, and EI Index ................................................... 75
   4.5.8 Peak Demand Conditions and Performance Constraints ............................................... 75
4.6 Results and Discussion ......................................................................................................... 75
   4.6.1 Pareto-Front Analysis ....................................................................................................... 75
   4.6.2 Sensitivity Analysis .......................................................................................................... 83
4.7 Broad Design Implications and Future Work ....................................................................... 87
4.8 Summary and Conclusions .................................................................................................. 87
4.9 References ............................................................................................................................ 87

Chapter 5: Summary and Conclusions ......................................................................................... 91
List of Figures

Figure 1.1: General overview of the EIO-LCA model applied to the example of iron pipe production............................................................................................................................................. 4

Figure 2.1: The chromosome/gene layout of a genetic algorithm solution consisting of w decision variables........................................................................................................................................... 15
Figure 2.2: Dominance, non-dominance, and Pareto-optimality for a multi-objective optimization in which both objectives are minimized.................................................................................................................. 16
Figure 2.3: Overview of the NSGA-II method (Process details described in Sections 2.6.1 to 2.6.6)......................................................................................................................................................................... 19
Figure 2.4: An example of the NSGA-II non-dominated sorting procedure................................................................. 20
Figure 2.5: NSGA-II tournament selection without replacement. ....................................................................................... 23
Figure 2.6: NSGA-II two-point crossover ................................................................................................................................. 24
Figure 2.7: NSGA-II selective mutation ................................................................................................................................. 25

Figure 3.1: Layout of test system..................................................................................................................................................... 45
Figure 3.2: Diurnal curve used in the test system. .............................................................................................................................. 48
Figure 3.3: Comparison of total cost (T) and pumping cost with environmental impact index for the hydraulically feasible design alternatives. .............................................................................. 52
Figure 3.4: Comparison of pipe cost with environmental impact index for the hydraulically feasible alternatives. .......................................................................................................................... 53
Figure 3.5: Average proportional contribution of pumping energy and pipe manufacturing to each environmental measure for all design alternatives. .................................................................................... 55

Figure 4.1: Anytown network with new tank at node 175 ..................................................................................................................... 70
Figure 4.2: Chromosome coding of Anytown solutions ................................................................................................................. 71
Figure 4.4: Proportional contribution of pumping energy, tank manufacturing, and pipe manufacturing to environmental measure totals for: a) “Low capital cost/high energy use” solution, and b) “High capital cost/low energy use” solution. .................................................................................... 80
Figure 4.5: Category index values for “Low capital cost/high energy use” solution, and “High capital cost/low energy use” solution. ................................................................................................... 82
Figure 4.6: Sensitivity of Pareto-optimal fronts: a) capital cost versus annual pumping energy use; b) annual pumping energy use versus EI index for baseline solutions and solutions with ±10% and ±30% variations in water demand.
List of Tables

Table 3.1: Environmental categories and environmental measures included in the environmental impact index. .................................................................................................................. 37

Table 3.2: Hypothetical example showing values of the SO₂ emission measure obtained for 13 WDS design alternatives. .............................................................................................................. 40

Table 3.3: Hypothetical example showing how the environmental impact index (EI) is calculated for a particular WDS alternative. ................................................................................................................................. 41

Table 3.4: Commercially available nominal and inner pipe diameters. ........................................................................................................................................................................ 46

Table 3.5: All design alternatives and associated design diameters, pipe cost, pump cost, total cost, cost ranking, pressure head during peak demands, environmental impact index, and environmental ranking. ................................................................................................................................. 50

Table 4.1: Environmental categories and environmental measures included in the EI index..... 64

Table 4.2: Chromosome decision variable specifications. ................................................................................................................................................................................. 71

Table 4.3: Cost of new cement-mortar lined ductile iron pipe, and cost of cleaning and lining existing pipe. ........................................................................................................................................ 72

Table 4.4: Tank volumes and construction costs. .................................................................................................................................................................................................. 73

Table 4.5: Pipe Hazen Williams ‘C’-factors in the first and second 10-year demand periods in Anytown. ................................................................................................................................. 74

Table 4.6: Environmental measure values per million dollar (purchaser price) worth of production of ductile iron pipe and tank manufacturing, and electric power generation........... 81

Table 4.7: Capital cost, annual pumping energy use, EI index, and cost breakdown for: 1) “Low capital cost/high energy use” solution, and 2) “High capital cost/low energy use” solution (all costs in million dollars). ............................................................................................................................................................................. 82
Chapter 1
Introduction

1.1 Introduction

The aging state of water distribution infrastructure in North America combined with an increase in water demand resulting from urban sprawl has led to a decline in the condition of water distribution systems (WDS). Deteriorating WDSs lead to increased operational and maintenance costs, water losses, a lower service level, and diminished water quality (Kleiner et al. 1998). In an attempt to address this situation, municipalities are expanding WDSs to improve service and satisfy growing consumer demand and expectations.

The WDS expansion problem involves the enhancement of system capacity through the duplication of pipes along road or right-of-way corridors; the addition of pipes where pipes did not previously exist (as in new developments); the cleaning and lining of existing pipes; and the addition of pumps and water storage tanks. By increasing system capacity, the WDS is better equipped to handle expected consumer demands and maintain a high level of service. The expansion of a WDS is a one-time expenditure that occurs at the beginning (time zero) of a planning period identified by a water utility. Expansion is different than other forms of WDS improvement such as rehabilitation, which considers the timed staging of repairs, cleaning and lining, and replacement over the entire lifetime of a WDS (Kleiner et al. 1998).

Although WDS expansion serves the function of decreasing operating costs by increasing hydraulic efficiency, the capital cost of WDS expansion is substantial. Municipalities are responsible for the financing of WDS expansion, but with strict municipal budgetary constraints and limited provincial and federal infrastructure grants, it is becoming increasingly difficult for municipalities to finance WDS expansion (AMO 2001). In addition to cost constraints in WDS expansion, municipalities must ensure that a given WDS expansion meets adequate demand under irregular conditions such as unusually high demand, or pipe breaks.

Recently, environmental concerns such as climate change have raised the attention of international bodies, national, provincial, and municipal governments, and individual citizens.
The United Nations Framework Convention on Climate Change (UNFCCC) is an international treaty that includes the Kyoto Protocol and recognizes the necessity of an international commitment to effectively reduce climate change and cope with the negative current and future cross-border effects of climate change (UNFCCC 2008). The Kyoto Protocol commits signing parties to stabilize their climate change causing greenhouse gas (GHG) emissions, and as a result parties have responded with individual climate change policies. These policies generally commit to a significant reduction in greenhouse gas emissions through a number of initiatives. For example, the European Union has committed to a 20% reduction from 1990 levels by 2020 and has implemented a carbon emissions trading scheme to aid in reaching this target (European Union 2009). Although some national governments, such as Canada and Australia, are still in the process of defining firm emissions frameworks and acceptable targets, Canadian provinces and municipalities are being pressed by environmentally-conscious constituents to implement independent emissions and pollution policies. In Canada, the provincial government of British Columbia addressed local climate change concerns by implementing an emissions-based carbon tax to all non-renewable fuel purchased in the province (Ministry of Small Business and Revenue 2008). In addition, some states in the United States have joined to develop the Regional Greenhouse Gas Initiative, a state-level emission and capping and trading program (RGGI 2005) and California has agreed to significantly reduce emissions as part of a newly state-passed Global Warming Solutions Act (EDF 2008).

The environmental impacts resulting from the production of electricity used to operate municipal WDSs are considerable. In the United Kingdom (UK), water distribution and sewerage operation activities are responsible for approximately 1% (or 6 million tons) of all GHG emissions (Ofwat 2008; DEFRA 2008). Recognizing the significant GHGs emitted by WDSs, the UK Water Services Regulation Authority (Ofwat), has required that water providers report on annual GHGs to allow for the framing of future WDS related climate change policy (Ofwat 2008). Ofwat has also recognized the need to address the additional non-operational GHGs resulting from the production and manufacturing of water distribution network components such as pipes, tanks, and pumps. It is anticipated that the cost increases incurred by WDSs as a result of environmental impact reducing policies, such as carbon taxes, will influence municipal WDS expansion decisions in the future. Therefore, in addition to the funding concerns and system performance
requirements mentioned above, municipalities must also address environmental impacts, such as climate change, air pollution, etc. related to WDS expansion and operation.

Climate change concerns have caused environmental policy makers to focus on greenhouse gas emissions; however further impacts stem from other environmental releases. Boyd and Genuis (2008) attributed a substantial number of Canadian cases of respiratory disease, cardiovascular disease, cancer, and low birth weights to adverse environmental exposures. One possible reason for the popularity of GHG policy is its focus on energy consumption and the ease with which it is estimated by electricity and fuel consumption. Other environmental releases are not quantified as easily which makes it difficult for policymakers to tackle these issues. One method of addressing the need for quantifying environmental releases linked to material extraction and product manufacturing is life cycle assessment (LCA). LCA quantifies the full range of environmental and social damages linked to a product or service by analyzing their raw material extraction, operation/use, transport, and disposal activities. The LCA method presents a comprehensive method of quantifying environmental impacts related to life-cycle activities of a product. However, it is expensive, time consuming, and requires a significant amount of data to perform. The other drawback of LCA is the arbitrary selection of the system boundary prior to the analysis of a product or process. Since boundary selection determines which industrial sectors and activities are included and excluded, it often has a significant impact on the solution and decision recommendations (Hendrickson et al. 2006).

The economic input-output-life cycle assessment (EIO-LCA) model has been developed to circumvent the data and boundary problems of the LCA method. The EIO-LCA model combines economic input-output (IO) models with LCA to produce a method for determining the environmental impacts resulting from each dollar spent in a given industrial sector. EIO models are mathematical tables, or matrices, that trace all direct and indirect industry supply chains (inputs and output), from material extraction to the point of sale, required to create a monetary unit of output in a given economic sector that produces a specific commodity such as iron pipe or electrical power. The EIO tables can be used to calculate the economic output of each sector required to satisfy final demand for the commodity produced by that sector. The EIO-LCA method shown in Figure 1.1, as applied to iron pipe production, multiplies the vector of sector outputs by an environmental burden matrix to obtain the environmental impact resulting from
each economic sector output resulting from iron pipe production. The environmental burden matrix comprises coefficients that represent the environmental impact per dollar of sector output for each sector. A different environmental burden is used for each environmental impact of interest. One drawback of EIO-LCA is that it uses aggregate data for a sector rather than the detailed situation-specific data used in LCA. For example, the EIO-LCA table does not differentiate between energy generated by a windmill and energy generated by a nuclear power plant. However EIO-LCA is computed by matrix multiplication and matrix inputs are better defined than LCA inputs. EIO-LCA also includes the input and output relationships of the entire economy which largely avoids the arbitrary boundary selection problems of the LCA method (Hendrickson et al. 2006).

Figure 1.1: General overview of the EIO-LCA model applied to the example of iron pipe production.
WDS expansion problems are complex and many design alternatives spaces that could never be explored by enumerating solutions one at a time. Incorporating multiple objectives such as minimum cost, maximum performance, and minimum environmental impact further complicates the problem. In order to handle the large number of possible solutions and competing objectives in WDS expansion problems, multi-objective optimization techniques have been implemented (Halhal et al. 1997; Walters et al. 1999; Wu and Walski 2005; Kapelan et al. 2006; Dandy et al. 2008). A multi-objective optimization balances competing objectives to identify feasible solutions that simultaneously meet all objectives. Multi-objective genetic algorithms (MOGAs) have been applied extensively to WDS expansion problems. MOGAs simulate the evolutionary processes of genetic selection, crossover, and mutation to arrive at the “fittest” solutions to the problem in a computationally efficient manner. The result is a number of fit solutions that balance all WDS expansion objectives. Stakeholders can use these optimization results in their decision making to choose a solution that best meets their concerns and priorities. Multi-objective optimization and genetic algorithms and their application to WDS expansion optimization are further explained in Chapter 2.

Recently, in an attempt to address the need to minimize the environmental impact resulting from WDS expansion, researchers have applied genetic algorithm-based multi-objective optimization to balance cost, performance, and environmental concerns in WDS expansion problems. Approaches have considered single environmental objectives, one at a time, such as minimizing greenhouse gas emissions (Wu et al. 2008, 2009) or embodied energy in material production and pipe manufacturing (Dandy et al. 2006, 2008) but none have considered multiple environmental impacts. The importance of considering multiple environmental impacts lies in the need to prevent environmental problem-shifting wherein the focus on one environmental objective (e.g., reducing greenhouse gas emissions) results in the worsening of another environmental objective (e.g., reducing toxic releases to water). Therefore, there is a need for a multi-objective optimization approach that allows water utility decision-makers to consider multiple environmental impact measures along with cost and performance in water distribution expansion.
1.2 Thesis objectives
This thesis presents a new approach to optimize the expansion of WDSs to arrive at system solutions that are cost effective and meet consumer demands and expectations while minimizing multiple environmental impacts. The thesis objectives are:

1. To develop a method that aggregates multiple environmental impact measures into a single environmental impact index that can be easily interpreted by water utility decision makers. The aim is to incorporate the environmental impact index into a multi-objective optimization approach to avoid environmental problem-shifting in decision making.
2. To develop a multi-objective WDS expansion optimization approach that considers cost, energy use, and environmental impact objectives.

1.3 Original Thesis Contributions
The research contributions made in this thesis are listed below:

1. An environmental impact (EI) index was developed to consolidate multiple environmental measures into a single index value. The EI index is unique in the water distribution system analysis research field.
2. The EI index was incorporated into the multi-objective non-dominated sorting genetic algorithm-II (NSGA-II) optimization to solve the WDS expansion problem.
3. The EI index/multi-objective optimization approach was applied to the realistic “Anytown” benchmark expansion problem (Walski 1987). Preliminary results from the “Anytown” benchmark problem suggest that including environmental impacts in WDS expansion optimization can result in solutions with lower energy use than solutions obtained through an optimization in which environmental impacts are not considered.

1.4 Thesis Organization
The thesis conforms to the School of Graduate Studies and Research manuscript format guidelines and is organized as follows:

Chapter 2 provides a brief overview of single and multi-objective optimization approaches applied to the WDS expansion problem. This chapter also provides an overview of the non-
dominated sorting genetic algorithm-II (NSGA-II) multi-objective optimization program which has been used in this thesis research.

Chapter 3 provides a detailed description of the development of the environmental impact (EI) index. This chapter provides an outline of criteria that should be addressed when assessing the environmental impact of WDSs. The EI index method is then described in detail within the context of a simple example to further demonstrate the required calculations. The role of the EI index in the multi-objective WDS expansion optimization framework is outlined. A simple four-pipe water distribution expansion problem is used to demonstrate the application of the EI index to the WDS expansion problem. EI index values are calculated and compared with capital pipe and lifetime energy costs of each system solution to demonstrate how the EI index can be used to guide the decision-making process in WDS expansion scenarios. Chapter 3 is based on a journal paper that has been accepted for publication in the September 2009 issue of the ASCE Journal of Infrastructure Systems. The title of Chapter 3 differs from the abovementioned journal paper on which it is based. The title of the publication as it will appear in the Journal of Infrastructure Systems is “Evaluating Environmental Impact in Water Distribution System Design.” The title of Chapter 3 of this thesis is “Developing and Applying an Environmental Impact Index for the Design and Expansion of Water Distribution Systems.”

Chapter 4 incorporates the EI index into a multi-objective WDS expansion optimization program where capital costs, annual pumping energy use, and the EI index are objectives to minimize. An abbreviated overview of the EI index is first provided, followed by the problem formulation of the three optimization objectives and constraints. Then a brief review of research that has implemented multi-objective genetic algorithms and specifically the non-dominated sorting genetic algorithm-II (NSGA-II) in WDS expansion is provided. The proposed triple objective optimization approach is then applied to the benchmark ‘Anytown’ problem from the water distribution system analysis literature. Detail is provided regarding the way in which costs, energy expenditure, and environmental impacts are calculated in the approach. Results are analyzed to determine the influence of the EI-based optimization on optimized solutions when compared with solutions obtained through optimization in which the EI index is not considered. Chapter 4 is based on a journal paper that was submitted in July 2009 to the ASCE Journal of Water Resources Planning and Management.
Chapter 5 concludes the thesis with an overview of the major research results and contributions. In addition, future research recommendations are provided to investigate additional applications of the new approach in WDS expansion optimization.

1.5 Journal and Conference Publications Related to the Thesis

As mentioned above, the contributions of this thesis have been incorporated in scientific papers submitted to international journals and international conferences. The current status of these publications is indicated below:


1.6 References


Chapter 2
Literature Review: Multi-Objective Genetic Algorithms and the NSGA-II in WDS Expansion

2.1 Introduction

Water distribution system (WDS) expansion addresses the need for increased capacity in systems that cannot adequately meet current and future consumer demands. The WDS expansion problem encompasses the following activities:

1. The addition of new pipes in areas slated for new development;
2. The cleaning and lining of existing system pipes;
3. The addition of duplicate pipes to the existing system;
4. The addition of new tanks to the existing system.

Most WDS expansion problems are complex, including a number of possible solutions for a given system layout. For example, if 32 pipes are to be added to a WDS and there are 10 commercially-available pipe diameters, there are $10^{32}$ possible system solutions. Each of these solutions will feature a total capital and operating cost and may or may not meet hydraulic constraints. To address this challenging problem, a number of optimization techniques have been developed to efficiently search for the optimal solution from a large set of possible WDS solutions.

2.2 Overview of Enumeration, Linear Programming, Steepest Descent, and Stochastic Search Techniques in Single Objective Optimization

The earliest WDS expansion optimization approaches were applied to the single-objective optimization of WDS expansion. The aim of single-objective WDS expansion optimization is to find the optimal least-cost solution that meets all hydraulic constraints under specific design demands. Optimization approaches explored in WDS expansion problems can be grouped into the four categories of enumeration, linear programming, steepest-descent, and stochastic search approaches (Savic and Walters 1997).
The enumeration approach explores every possible solution in the solution space to identify the optimal solution. This technique is inefficient for large solution spaces such as those that exist in the WDS expansion problem. For example, supposing it takes 1/60 of a second to enumerate each of the $10^{32}$ solutions listed in the simple example above, it would take $5.3 \times 10^{22}$ years to solve the problem. It is possible to narrow the solution space by eliminating infeasible solutions from the WDS search space and then enumerating the remaining solutions (Gessler 1985). However, this method requires *a priori* knowledge of the system as well as expertise and has failed to find optimal solutions even in small WDSs (Simpson et al. 1994; Savic and Walters 1997).

Recognizing the inefficiency of the enumeration method, Alperovitz and Shamir (1977) developed a linear-programming approach that simplified the non-linear WDS expansion problem into a linear problem through a two-step iterative process. The linear programming method of Alperovitz and Shamir (1977) evaluates the derivatives of WDS expansion cost with respect to changes in flow distribution to determine the minimum cost solution for a given WDS. The linear-programming approach proposed by Alperovitz and Shamir (1977) was further refined by Quindry et al. (1981), Morgan and Goulter (1985), and Fujiwara and Khang (1990).

Steepest descent approaches attempt to find minimum cost solutions in the WDS expansion problem by repeatedly evaluating derivatives of the cost objective function in the steepest descending direction and extrapolating them over finite increments until the lowest cost solution is found. A steepest descent technique was implemented by Lansey and Mays (1989) in a non-linear programming approach to find optimal solutions in a feasible WDS expansion search space. Steepest-descent approaches often fail to find the global minimum (least-cost solution) since they often become “trapped” in local minima in the complex solution space of the WDS expansion problem. Steepest-descent methods also rely on a continuous solution space to evaluate objective function derivatives; however, decision variables in the WDS expansion problem are discrete (e.g., set of discrete commercially-available diameters) and thus its solution space is discontinuous. To partly overcome these disadvantages, researchers have used the steepest-descent approach to refine solutions found by global search methods such as genetic algorithms (van Zyl et al. 2004).
Enumeration, linear programming, and steepest-descent methods are deterministic approaches which both require experience and a priori knowledge to simplify the solution space. They also require a number of time-consuming solution evaluations and iterations that may or may not lead to a global optimum (Savic and Walters 1997). To partly overcome these disadvantages, stochastic search techniques have been applied to the WDS expansion problem. Stochastic search techniques are well-suited to the non-linear, multi-dimensional, discrete characteristics of the WDS expansion problem because they employ random selection. This encourages diverse solution sampling and often leads to solutions at or near the global minimum (Goldberg 1989).

Simulated annealing is a stochastic search method that has been applied to WDS optimization. In simulated annealing, a solution is randomly selected from the WDS solution space and is then modified slowly through a process based on the technique of annealing in metallurgy, which involves the controlled heating and cooling of metals to create crystalline structures. In each step of the simulated annealing algorithm, the current solution is replaced by a random but similar solution chosen with a probability that depends on the current solution and temperature parameter, $T$, which is gradually increased throughout the annealing process (Cunha and Sousa 2001). The primary disadvantage of simulated annealing is that it is sensitive to variability in the chosen temperature parameter and the speed of adjustment of this parameter (Cunha and Sousa 2001). As a result, it has had limited application in the area of WDS optimization. The need for an efficient, simple, and powerful single-objective optimization method that could be applied to the WDS optimization problem was eventually met with the introduction of genetic algorithms.

2.3 Overview of Genetic Algorithms in Single-Objective Optimization

The genetic algorithm (GA) is an optimization tool that is based on the natural phenomenon of evolution whereby the “fittest” individuals of a population have the best chance of surviving and reproducing. When applied to the single-objective least-cost WDS expansion problem, GAs efficiently search a solution space to identify the “fittest” (the lowest cost) WDS expansion solutions through computer-simulated versions of genetic selection, crossover, and mutation (Goldberg 1989). The GA searches the solution space efficiently but does not test every single possible solution. Thus it is possible that the “least-cost” solution, or global optimum, may not be found (Savic and Walters 1997). Despite this, researchers have demonstrated that for most problems, the global minimum or solutions near the global minimum can be found with GAs.
Since in this thesis a multi-objective genetic algorithm approach is developed, only a brief overview of single-objective genetic algorithms in WDS expansion is given.

In the last 15 years, researchers have applied GAs to solve the single-objective “least-cost” WDS design and expansion problem (Simpson et al. 1994; Dandy et al. 1996; Savic and Walters 1997; Vairavamoorthy and Ali 2000; Wu et al. 2001; Wu and Simpson 2001; Wu and Simpson 2002; Farmani et al. 2005c; Afshar and Marino 2007). The aim of this earlier research was to develop optimization algorithms to minimize capital costs (pipe, pumps and tanks) and operation costs to meet hydraulic requirements under a number of known demand conditions in WDS expansion. More recently, single-objective GAs have been developed to achieve more robust network designs under uncertainty in water demand and pipe failures (Walski 2001; Kapelan et al. 2004; Tolson et al. 2004; Babayan et al. 2005).

2.4 Multi-Objective Genetic Algorithms: Problem Definition

In the last ten years, there has been a growing recognition in the field of water distribution system analysis that pipe and pumping cost objectives should be supplemented with additional objectives such as hydraulic reliability, water quality, and environmental performance (Walksi 2001). Very recently, multi-objective genetic algorithms have been used to incorporate multiple objectives in the WDS expansion problem. Multi-objective genetic algorithms (MOGA) are conceptually similar to single-objective genetic algorithms (SOGA) in that solutions are evolved through computer-simulated versions of genetic selection, crossover, and mutation. The difference between these two optimization approaches is that the MOGA considers two or more objectives while the SOGA only considers one objective. MOGA optimization is designed to generate a set of solutions that balance two or more conflicting objectives while the SOGA optimization generates a single solution that minimizes a single objective. Srinivas and Deb (1994) mathematically stated the multi-objective problem as follows:

Objective functions:

\[
\text{Minimize or maximize: } f_i(\bar{x}) \quad i = 1, 2, ..., n
\]  

Constraints:

\[
\text{Subject to: } \quad g_j(\bar{x}) \leq 0 \quad j = 1, 2, ..., p
\]

\[
\text{and } \quad h_k(\bar{x}) = 0 \quad k = 1, 2, ..., q
\]
where \( n \) = the number of objective functions; \( p \) = the number of inequality constraints; and \( q \) = the number of equality constraints.

The parameter \( \vec{x} \) is a vector featuring decision variables \( x_1, x_2, \ldots, x_w \), where \( w \) is the total number of decision variables—also called genes in a GA—each of which must be chosen from a list of possible values (e.g. commercially available pipe diameters). Together, these \( w \) decision variables (or genes) make up one system solution, also called a chromosome in a GA. A chromosome consisting of \( w \) genes is depicted in Figure 2.1. Each solution is evaluated by the GA to determine the value of its \( n \) objective functions. A brief example of the gene-chromosome structure and objective function evaluation is given next. Suppose that ten new pipes must be added to an existing WDS system. Thus, in this problem, a single solution or chromosome has 10 decision variables (\( w \)) or genes. The diameter of a new pipe is selected from 12 commercially-available pipe diameters. The total enumeration of possible solutions is thus the number of commercially-available pipe diameters for each new pipe raised to the power equal to the number of new pipes added, or \( 12^{10} \approx 62 \) billion solutions. Further, the system is to be optimized with two objectives: 1) minimize pipe cost, and 2) minimize operating cost. Each unique system solution (chromosome) will feature a different combination of 10 pipe diameters (genes) and will correspond to unique values of pipe cost (objective 1) and operating cost (objective 2). A further example of the chromosome layout in a WDS solution can be found in Chapter 4, Figure 4.2.

![Figure 2.1: The chromosome/gene layout of a genetic algorithm solution consisting of \( w \) decision variables.](image)
Multi-objective optimization algorithms generate a set of solutions called a Pareto-optimal front which consists of non-dominated solutions (Srinivas and Deb 1994). If all objectives are to be minimized, one solution (“Solution 1”) will dominate another solutions (“Solution 2”) if all of the objective function values of Solution 1 are less than or equal to Solution 2 and at least one of the objective function values of Solution 1 is strictly less than Solution 2. Therefore, an objective function value of a Pareto-optimal solution cannot be improved without compromising at least one of the other optimization objectives. In a MOGA, solutions pairwise comparison occurs and the conditions for dominance create situations in which neither solution dominates the other, thereby resulting in multiple non-dominated solutions and, ultimately, the Pareto-optimal front (Srinivas and Deb 1994). The concept of dominance is indicated in Figure 2.2. Figure 2.2 presents two objectives, Objective 1 and Objective 2, which have been minimized, resulting in a Pareto-optimal front. Solutions A and B are non-dominated solutions and therefore, they reside on the non-dominated Pareto-optimal front. Solution A dominates solution C because Solution A results in an improvement in Objective 1 with no change in Objective 2 when compared with Solution C. Solution B dominates solution C because Solution B results in an improvement in Objective 2 with no change in Objective 1 when compared with Solution C. As a result, Solution C is dominated and thus, is not part of the Pareto-optimal front.

![Dominance, non-dominance, and Pareto-optimality for a multi-objective optimization in which both objectives are minimized.](image)

**Figure 2.2:** Dominance, non-dominance, and Pareto-optimality for a multi-objective optimization in which both objectives are minimized.
A MOGA-generated Pareto-optimal front allows decision-makers to choose from a set of non-dominated solutions rather than a single optimal solution as in single-objective optimization. Further, MOGA optimization allows decision-makers to analyze solutions in a post-optimization process and choose feasible solutions from a Pareto-optimal front that best meet the overall needs of stakeholders (Srinivas and Deb 1994; Cheung et al. 2003). When applied to WDS expansion, MOGA optimization can generate solutions that minimize pipe and operating cost objectives alongside other environmental objectives.

2.5 Multi-Objective Genetic Algorithms in WDS Design Optimization Research

Early MOGA methods applied to WDS optimization implemented various forms of the “messy” GA (Halhal et al. 1997; Walters et al. 1999). The messy GA incorporates a “messy” chromosome coding that preserves schemata in GA solutions. Schemata are common adjacent sequences of decision variable values, referred to as building blocks, that are present in a number of optimal solutions; when preserved, these schemata have the potential to form the foundation for good solutions. By identifying and preserving schemata as they arise throughout the MOGA optimization process, the best solution components can be maintained across multiple generations to arrive at optimal solutions more efficiently (Goldberg et al. 1993). Multi-objective messy GAs applied to WDS expansion by Halhal et al. (1997) and Walters et al. (1999) included a cost objective and a benefit objective that incorporated the pressure, maintenance, operational, and quality benefits associated with new, parallel, cleaned and lined pipes, and additional storage and pumping capacity.

Wu and Walski (2005) added a constraint-handling technique to the messy MOGA approach, which integrated constraints as adaptive penalties wherein a particular objective value would be penalized for not adhering to a WDS system constraint such as minimum head loss requirements. Prior to the adaptive penalty approach, penalties applied to objective functions in GA optimizations required the a priori specification of a penalty factor. In these non-adaptive penalty approaches, the penalty factor chosen determines the extent of the penalty applied to each constraint-violating solution. If penalties are too severe, acceptable solutions may be eliminated from the optimization and if penalties are too relaxed, unacceptable solutions will remain and will ultimately affect the final Pareto-optimal front. Choosing an appropriate penalty factor requires
the testing of a number of values, which is time-consum ing and can be subject to user bias. The adaptive penalty approach does not require the \textit{a priori} selection of a penalty factor and instead adapts the penalty factor over the course of the optimization eliminating the need for a fine-tuning process (Wu and Walski 2005). Although the messy GA constraint-handling technique implemented by Wu and Walski (2005) was effective in producing acceptable WDS solutions, the method required additional computer coding, which complicated the simplicity of the GA coding and search behaviour.

\textbf{2.6 Overview of the Non-Dominated Sorting Genetic Algorithm (NSGA-II)}

The need for an efficient and effective MOGA that could handle highly constrained, discrete, non-linear WDS optimization problems led to the acceptance of the non-dominated sorting genetic algorithm-II (NSGA-II) (Deb et al. 2002) over other MOGA methods (Farmani et al. 2005b). The advantage of the NSGA-II over other methods is in its simple and effective constraint-handling technique. Other advantages of the NSGA-II include: i) the accelerated speed of the non-dominated sorting approach, ii) the ability to preserve good solutions throughout the evolution process, and, iii) the lack of a need for the \textit{a priori} specification of parameters. A detailed description of the NSGA-II is provided by Deb et al. (2002). The working of the NSGA-II is depicted in Figure 2.3 and briefly described below where \( t \) represents the current generation and \( t+1 \) represents the next generation.
2.6.1 Initial population

Before a genetic algorithm begins its search, an initial population must be generated. The initial population (comprised of system solutions called chromosomes) is generated randomly to ensure diversity in the starting population. The population size, \( N \), for a particular problem is pre-specified by the user and is held fixed throughout the optimization run. The initial random population for the NSGA-II is double the size, \( 2N \), of a normal population, which ensures additional diversity of the initial population (Deb et al 2002).

2.6.2 Non-dominated sorting of the initial population

The initial generation, \( t \), is shown in Figure 2.3 and consists of a population, \( P_t \), of size \( N \) and a second population, \( Q_t \), of size \( N \). This initial double population is sorted into fronts with the non-
dominated sorting procedure (explained next) of the NSGA-II. The basis of this procedure is to evaluate the objective functions of each solution in the initial population relative to other solutions in the initial population, organize the solutions according to their dominance over one another, and choose a population, $P_{t+1}$, of size $N$ from the initial population, of $2N$.

Figure 2.4 presents an example of the non-dominated sorting of population of five solutions into three fronts. The procedure begins by evaluating each solution, $p$, in the initial population to determine the number of solutions, $n_p$, that dominate each solution $p$ and a set of solutions, $S_p$, that are dominated by $p$. All solutions with $n_p = 0$ will be in the first non-dominated front (front 0) and each of these front 0 solutions will feature its own set $S_p$. For each member of front 0, the value of $n_p$ for each solution in the set $S_p$ is reduced by one. All solutions in $S_p$ with $n_p = 0$ will be in the next non-dominated front (front 1). This de-incrementing procedure continues for each consecutive front until all solutions have been placed in a front (front 2, front 3, …) (Deb et al. 2002).

**Figure 2.4:** An example of the NSGA-II non-dominated sorting procedure.
2.6.3 Post-sorting population

Figure 2.3 shows how a post-sorting population, $P_{t+1}$, is selected from the non-dominated sorted population of size $2N$. This population $P_{t+1}$ can only comprise $N$ population members. Therefore, $N$ solutions are chosen from the double initial population ($P_t + Q_t$) starting with the first front, front 0, and continuing to the next fronts (front 1, front 2, …) until $N$ solutions have been chosen for the new population, $P_{t+1}$. In some cases, including all front members of the last chosen front of the initial population results in more than $N$ chosen solutions. Only $N$ solutions can be chosen and all members of the last chosen front are equally as non-dominated, resulting in the need to implement a crowding distance comparison procedure to compare solutions from the same front.

The crowding distance is a measure of how similar a solution is to another solution in the same front when all objective functions are compared. A longer crowding distance denotes a solution that is further away from other front solutions and these solutions are preferred as they preserve diversity in the newly chosen population. The crowding distance of each solution in the last chosen front is calculated and the front is organized in descending order of crowding distance. The solutions from the last chosen front with the largest crowding distance values are chosen for the population $P_{t+1}$ and the other front solutions are discarded (Deb et al. 2002).

2.6.4 Selection, Crossover, Mutation

At this point, the selection procedure has identified the “fittest” members of the initial population based on non-dominated sorting and the crowding-distance comparison method. To further improve the population, the resulting population $P_{t+1}$ is subject to the genetic operations of selection, crossover, and mutation to create a new population, $Q_{t+1}$, as shown in Figure 2.3. There are a number of methods that can be used for each genetic operation of the NSGA-II procedure. However, only the methods applied in this study are described below.

Selection: Tournament Selection Without Replacement

Tournament selection is the process by which a user-specified number of population members of the population $P_{t+1}$ are selected randomly. The best (dominant) individual from this chosen sample continues on for further operations such as crossover and mutation and the process is repeated for the rest of the population members. Therefore, the purpose of the selection process
is to identify the fittest members of the sorted population. Figure 2.5 depicts tournament selection without replacement featuring a tournament size of two for simplicity. Members are first shuffled and then compared two at time until all members have been compared once. The population is then shuffled a second time and each member is compared again to arrive at a selected population of size $N$. The result of the selection process is a new population with some of the best randomly chosen members of the population $P_{t+1}$ (Goldberg and Deb 1991).
Figure 2.5: NSGA-II tournament selection without replacement.
Crossover: Two-Point Crossover

The new population resulting from the selection of population $P_{t+1}$ is subject to the crossover process whereby two parent population members are “crossed” to create two child population members with each child containing part of each parent’s solution. Two-point crossover is depicted in Figure 2.6. The two-point crossover process randomly chooses two members, or parents, from the newly selected population, splices each of their chromosomes (solutions) at two randomly chosen crossover sites, and switches the genes (decision variables) between these sites to create two new children each containing part of both parental chromosomes (Halhal et al. 1997).

![Figure 2.6: NSGA-II two-point crossover.](image)

Mutation: Selective Mutation

The child population resulting from the selection and crossover of the previous population is based on the initial randomly chosen population and thus bears characteristics of that initial population. Although the random initial population provides a good sample of the entire solution space, additional solution diversity is ensured by the random process of mutation. A random mutation operator introduces solutions into the population that may not be created through the selection and crossover processes, but may be “fitter” than those solutions in the current
population. The mutation operator also restores individual decision variable values that may have been lost in previous generations. Figure 2.7 shows the selective mutation process, which randomly selects a decision variable of a solution from a child member and replaces the decision variable with a random variable within a specified range. In the example shown in Figure 2.7, decision variables can have a value of either 0 or 1. Mutation of each solution in the child population occurs with a pre-specified probability (Herrera et al. 1998).

<table>
<thead>
<tr>
<th>Decision variables</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Decision variable values of solution</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

![Mutate decision variable 3]

**Figure 2.7: NSGA-II selective mutation.**

### 2.6.5 Recombination and reevaluation

Once selection, crossover, and mutation have occurred, a population, $Q_{t+1}$, of size $N$ results (Figure 2.3). This population is combined with the population $P_{t+1}$ to create a population $(P_{t+1} + Q_{t+1})$ with a size of $2N$. This combined population is subject to another non-dominated sorting and $N$ solutions are chosen for the next population using a crowding comparison operator to compare solutions in the same front, if necessary. Therefore, the resulting population consists of the best solutions from the newly formed population as well as best solutions from the previous population that may have been lost through the selection, crossover, and mutation operations. The newly formed population undergoes selection, crossover, and mutation and then recombination and reevaluation in subsequent generations to eventually arrive at the Pareto-optimal front. The chosen generation number for NSGA-II-based WDS expansion optimization models in the literature is highly variable; however convergence is often observed within 200 generations (Formiga et al. 2003; Wu and Walski 2005; Kapelan et al. 2006, Dandy et al. 2008).
2.6.6 Constraint handling

When constraints, such as minimum pressure head requirements, exist for a given problem, solutions that meet constraints are designated “feasible solutions” and those that do not meet constraints are designated “infeasible solutions”. An effective constraint-handling approach based on tournament selection was proposed in the NSGA-II by Deb et al. (2002). This tournament-based constraint handling technique is implemented within the non-dominated sorting procedure depicted in Figure 2.4, wherein Solutions A and B are being compared for dominance and Solution A dominates Solution B under any one of the following conditions:

1. Solution A is feasible and Solution B is infeasible
2. Both solutions are infeasible and Solution A has a lower total constraint violation than Solution B
3. Both solutions are feasible and Solution A dominates Solution B (this is the scenario shown in Figure 2.2)

2.7 Application of the NSGA-II in WDS Design Research

In the past five years, researchers have exploited the simple constraint-handling characteristics of the NSGA-II to tackle the complex WDS expansion problem. Here, the NSGA-II has been applied to water networks with a capital cost objective and additional network performance objectives and head loss constraints. Formiga et al. (2003) applied the NSGA-II to a WDS expansion study wherein pipe cost, flow path redundancy, and system demand-supply ratio were included as conflicting objectives. Farmani et al. (2005a,c) applied the NSGA-II to investigate the relationship between the total present value of system costs (pipes, pumps, tanks, pressure valves) and system reliability, and between total system cost and minimum surplus head violations. In some cases the NSGA-II has been modified and coupled with other optimization techniques to improve its search capability (Nicolini 2005) and to guide WDS expansion toward solutions that are more robust and better able to deal with demand and uncertainty (Kapelan et al. 2006).

Researchers have also adopted the NSGA-II to incorporate environmental impacts into the multi-objective WDS expansion problem. Wu et al. (2008, 2009) used the NSGA-II to minimize the total present value costs of a WDS while minimizing the social cost of greenhouse gas emissions resulting from pipe manufacturing and operating emissions. Dandy et al. 2008 used the NSGA-II
to investigate the relationship between the cost of PVC pipes and the embodied energy of the pipes in WDS expansion\(^1\). Herstein et al. (2009b) have incorporated an environmental impact index objective developed elsewhere (Herstein et al. 2009a) into the NSGA-II. The environmental impact index and the NSGA-II model were used to minimize a capital cost objective, a pumping energy objective, and an environmental impact objective in the WDS expansion optimization problem.

2.8 Summary

Multi-objective genetic algorithms have been used extensively in the optimization of water distribution systems. MOGAs have enabled researchers and practitioners to incorporate multiple objectives to balance cost, performance, and other concerns in WDS expansion optimization. In the last five years, the NSGA-II has been widely adopted in the field of water distribution system analysis owing to its efficient and straightforward sorting and constraint-handling characteristics. Recently, researchers have used the NSGA-II to incorporate environmental impact objectives into WDS design. Further research is needed to determine how best to weigh cost, performance, and environmental impact objectives to generate cost-effective WDSs that adequately meet consumer demands with minimal overall environmental impact.

2.9 References


\(^1\) Embodied energy denotes the energy required to convert the raw pipe material into a finished product.


Chapter 3
Developing and Applying an Environmental Impact Index for the Design and Expansion of Water Distribution Systems

Increasingly, decision-makers in water utilities are considering environmental impacts in the planning and design of water infrastructure. There are a number of environmental impacts linked to the expansion and design of water networks. For example, the manufacturing of pipes requires that materials be extracted, transported, and processed. These processes generate environmental discharges and consume non-renewable energy resources. In Chapter 3, an environmental impact (EI) index is developed to aggregate multiple environmental measures in water network expansion and design. The EI index was incorporated into a multi-objective decision framework in which total cost and the EI index were minimized to balance cost concerns with multiple environmental impact concerns. The EI-based multi-objective approach was applied to a simple water transmission system.

3.1 Abstract
An index-based method for the evaluation of the environmental impact of water distribution systems is introduced. The method is developed according to a set of methodological criteria to assess the environmental effect of water networks. A number of environmental measures are incorporated into the index-based method to account for non-renewable resource consumption, greenhouse gas emissions, and emissions to air, land, and water. The index method can be included into a multi-objective optimization program to find design solutions that minimize cost and environmental impact. The index-based method was applied to the design of a water transmission system over a 20-year design horizon. Design alternatives were compared on the basis of the environmental impact index and cost. For the system analyzed, results indicated that of the hydraulically feasible alternatives, the five most environmentally acceptable alternatives were the five most cost-effective alternatives. Results also showed that the environmental impact

____________________

2 This chapter is to be published in September, 2009, in the ASCE Journal of Infrastructure Systems under the title “Evaluating Environmental Impact in Water Distribution System Design.”
index is mainly influenced by pumping energy and partially influenced by pipe diameter selection.

### 3.2 Introduction

The traditional methods of optimizing water distribution systems (WDS) consider local concerns such as the cost of pipe, pump, and tank upgrades, and meeting minimum pressure head and maximum velocity requirements. Although these local concerns are important to any water utility, engineers are beginning to realize that environmental impact should also be included in WDS optimization. This is owing to the growing recognition that WDSs depend on regional energy and production systems in the construction, operation, and disposal stages. This dependency leads to environmental impacts that manifest themselves outside the physical and jurisdictional boundaries of a WDS over time. Therefore, added to the traditional concerns of minimizing cost and meeting hydraulic and water quality requirements are regional concerns of material and energy use, greenhouse gas emissions, and toxic releases associated with the production of network components and their continued operation.

One widely used method to incorporate environmental impact and environmental sustainability considerations into WDS design is Life Cycle Assessment (LCA). A process-based LCA method analyzes the environmental impact of a product over the entire period of its life cycle including extraction, manufacturing, use, and disposal (UNEP 1996). The use of LCA in assessing the environmental impact of WDS design has been explored in the literature. For example, Dennison et al. (1999) have implemented LCA to compare the environmental impact of different pipe materials. Others have used LCA to compare the overall environmental impact of different wastewater, stormwater, and drinking water system alternatives over a planning period for the purpose of decision-making (Lundie et al. 2004, 2005). The LCA method is often combined with other environmental impact measures to provide a more thorough assessment. Jeppsson and Hellstrom (2002) combined LCA with Material Flow Analysis (MFA), a method of tracking individual mass flows of a given system from material extraction to disposal.

In place of MFA, the economic input-output life-cycle assessment (EIO-LCA) technique can be used to quantify economy-wide environmental discharges linked to the fabrication of materials and components used in an engineering system. EIO-LCA traces monetary and material flows
between industry sectors that contribute directly and indirectly to the production of a given item or service. Filion et al. (2004) used EIO-LCA to quantify energy expenditures in the fabrication stage of a WDS while Stokes and Horvath (2006) used the same method to assess environmental impacts of WDS alternatives designed to address water shortages. Ghimire and Barkdoll (2007) have suggested applying eco-efficiency analysis to WDS optimization, which is a technique used for client-based alternative comparison, of which LCA is a component. The end result of eco-efficiency analysis is a relative measure of overall ecological destruction as a result of overall economic creation. Dandy et al. (2006) developed an optimization program that incorporates sustainability objectives of whole-of-life-cycle costs, energy use, greenhouse gas emissions, and resource consumption. The optimization program was applied to a real network in Australia, where the least-cost design was compared with the ‘environmentally sustainable’ design. The ‘sustainable’ design had a lower cost, a reduced rate of PVC material and energy use, and lower levels of greenhouse gas emissions.

This paper presents a new index-based method to assess the environmental impact of a water distribution system. The new method aggregates resource consumption (non-renewable energy use), environmental discharges (air pollutants, toxic releases to air, water, and land), and environmental impacts (ecological fossil-fuel footprint) into a single environmental impact index, which can be incorporated into multi-objective optimization to guide the design of water distribution systems. The paper is organized as follows. First, the paper outlines a set of criteria that any new method to assess the environmental impact of WDSs should meet. Second, the environmental impact index is presented along with the required methodological steps for its evaluation. Third, the inclusion of the environmental impact index into multi-objective optimization as an objective function to be minimized is discussed. Fourth, the index is applied to the design of a simple pump-pipe transmission system.

3.3 Criteria for the Environmental Assessment of Water Networks

3.3.1 Complete Life Cycle Assessment

To evaluate the environmental impact of a given WDS, the three life cycle stages of the WDS (fabrication, use, and disposal) should be considered. Indeed, the environmental impacts of a WDS go beyond operating the system. The material resource extraction and energy required to
manufacture the components of the system such as pipes and pumps also contribute to the environmental impact of the system. For example, Filion et al. (2004) found that the embodied energy linked to the fabrication of pipes in a network can in some cases be as important as energy used for pumping water. If data is available, the environmental impacts linked to the disposal of the system components should also be considered.

### 3.3.2 Functional Unit and Comparison of Alternatives

The functional unit of the analysis should be tied to the fundamental function of a WDS and its primary output. Since the fundamental function of a WDS is to supply and distribute water, the functional unit should be chosen to be the volume of water consumed by users of the system, in megalitres (ML), throughout its expected service life. The functional unit of water volume has the advantage of simultaneously accounting for population level and per capita water consumption factors that drive the energy use, material use, emission of air pollutants, etc. in all life stages of a system. The environmental performance of different alternatives can be assessed by dividing the impact/output/consumption level by the water consumed by users of the system.

### 3.3.3 Aggregation of Environmental Measures into a Single Index

There are a number of environmental measures that can be used to assess the impact of a given WDS design on the environment such as toxic releases, global warming potential, and non-renewable resource use. Considering a number of measures makes decision-making more difficult since an alternative might rank highly with respect to one measure but might be outranked by other alternatives with respect to other measures. For this reason, an environmental impact index that conveniently combines a number of measures (e.g., ecological footprint, environmental discharges, and non-renewable energy use) into a single index is appealing. Notwithstanding this, there are two important caveats to the use of an aggregate-scaled environmental impact index to guide the design and optimization of water networks. First, since an index value aggregates environmental impacts into a single parameter it is mute on whether all environmental impacts are minimized. For example, an index value indicating a high degree of system “sustainability” might be associated with a low global warming potential that compensates for high toxic releases to water. Second, the aggregation of environmental impacts into a single parameter does not guarantee that negative, long-term environmental or health consequences will be minimized.
3.3.4 Environmental Releases and Ecological Degradation

An environmental impact index should quantify environmental depletion (e.g., use of non-renewable energy resources, unsustainable use of renewable resources) and environmental discharges (e.g., air pollutants, aquatic discharges) and the effect those discharges have on human health and ecological systems in relation to the reduction of natural capital and/or capacity to receive and assimilate waste streams. Unfortunately, this information is not easily determined with certainty. Previous work by Boyd and Genuis (2008) has investigated the contribution of environmental pollutants to the overall disease burden in Canada. This measure is quite broad and makes it difficult to pinpoint the degree of burden specifically caused by WDSs. Other measures exist such as ecological footprint analysis, wherein products and practices are assessed in terms of the bioproductive area that would be required in order to absorb resulting fossil fuel emissions or to regenerate utilized renewable resources (Monfreda et al. 2004). While this measure can be easily applied to WDSs and is easily understood, it is only able to deal with the fossil fuel emissions resulting from any given WDS, which comprise only one component of environmental pollution; the other measures of toxic releases to land, air, and water are not considered in the ecological footprint method.

3.4 Environmental Impact Index

The new environmental impact index aggregates measures of resource consumption (non-renewable energy use), environmental discharges (air pollutants, toxic releases to air, water, and land), and environmental impacts (ecological fossil-fuel footprint) into a single parameter to guide the design of water distribution systems. In Table 3.1, these environmental measures are grouped into the four major environmental categories of air pollution, non-renewable energy depletion, fossil fuel footprint, and toxic releases. Table 3.1 also indicates the units of each measure per functional unit of megalitres of water delivered. For example, the environmental measure “coal consumption” under the environmental category “non-renewable resource depletion” in Table 3.1 has units of megaJoules/ML and quantifies the amount of energy derived from coal that is consumed to manufacture pressure pipe to deliver water to users during the service life of a system. All environmental measures and impact categories in Table 3.1 are based on and are evaluated with the online EIO-LCA model (Hendrickson et al. 1998) produced by the Carnegie Mellon University Green Design Institute (Carnegie 2008). The Carnegie Mellon online EIO-LCA has been chosen to demonstrate the environmental impact index methodology.
due to its widespread use and accessibility. The Carnegie Mellon online EIO-LCA includes Canadian, Spanish, and German versions of the model (Carnegie 2008) making the analysis proposed in this paper applicable to other countries. Details of this evaluation are discussed later in this paper.

Table 3.1: Environmental categories and environmental measures included in the environmental impact index.

<table>
<thead>
<tr>
<th>Environmental Category</th>
<th>Environmental Measure*</th>
<th>Type</th>
<th>Units/ML water conveyed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Air pollution</td>
<td>Sulfur dioxide</td>
<td>discharge</td>
<td>kilograms (kg)</td>
</tr>
<tr>
<td></td>
<td>Carbon monoxide</td>
<td>discharge</td>
<td>kg</td>
</tr>
<tr>
<td></td>
<td>Nitrogen oxides</td>
<td>discharge</td>
<td>kg</td>
</tr>
<tr>
<td></td>
<td>Volatile organic compounds</td>
<td>discharge</td>
<td>kg</td>
</tr>
<tr>
<td></td>
<td>Lead</td>
<td>discharge</td>
<td>kg</td>
</tr>
<tr>
<td></td>
<td>Particulate matter &lt; 10um</td>
<td>discharge</td>
<td>kg</td>
</tr>
<tr>
<td>Non-renewable energy depletion</td>
<td>Coal</td>
<td>consumption</td>
<td>megaJoules (MJ)</td>
</tr>
<tr>
<td></td>
<td>Natural gas</td>
<td>consumption</td>
<td>MJ</td>
</tr>
<tr>
<td></td>
<td>Liquefied natural gas</td>
<td>consumption</td>
<td>MJ</td>
</tr>
<tr>
<td></td>
<td>Liquefied petroleum gas</td>
<td>consumption</td>
<td>MJ</td>
</tr>
<tr>
<td></td>
<td>Motor gasoline</td>
<td>consumption</td>
<td>MJ</td>
</tr>
<tr>
<td></td>
<td>Distillate</td>
<td>consumption</td>
<td>MJ</td>
</tr>
<tr>
<td></td>
<td>Kerosene</td>
<td>consumption</td>
<td>MJ</td>
</tr>
<tr>
<td></td>
<td>Jet fuel</td>
<td>consumption</td>
<td>MJ</td>
</tr>
<tr>
<td></td>
<td>Residual</td>
<td>consumption</td>
<td>MJ</td>
</tr>
<tr>
<td>Fossil-fuel footprint</td>
<td>Ecological footprint</td>
<td>impact</td>
<td>metres squared of bioproductive forest land (m^2)</td>
</tr>
<tr>
<td></td>
<td>(volumetric)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Toxic releases</td>
<td>Total air releases</td>
<td>discharge</td>
<td>grams (g)</td>
</tr>
<tr>
<td></td>
<td>Water releases</td>
<td>discharge</td>
<td>g</td>
</tr>
<tr>
<td></td>
<td>Land releases</td>
<td>discharge</td>
<td>g</td>
</tr>
<tr>
<td></td>
<td>Underground releases</td>
<td>discharge</td>
<td>g</td>
</tr>
<tr>
<td></td>
<td>Total transfers</td>
<td>discharge</td>
<td>g</td>
</tr>
</tbody>
</table>

*All measures listed other than Ecological Footprint can be obtained directly from the Carnegie Mellon Green Design Institute’s online EIO-LCA tool (Carnegie 2008). These measures, as well as the Ecological Footprint, are divided by the volume of water (in ML) the system delivers to users during its service life.

It is noted that Table 3.1 features only one environmental impact measure, ecological footprint, which is based on global warming potential, or carbon dioxide (CO_2) equivalents of greenhouse gases emitted. Here, the ecological footprint is a measure of the bioproductive forest area required to sequester the CO_2 produced in the production of pipes and electricity used to operate the pumps in the system alternative being considered. The ecological footprint is calculated with the
where \( EF = \frac{GWP \times (1 - \text{fraction absorbed by ocean}) \times (10000 \, \text{m}^2/\text{ha})}{(\text{period}) \times (\text{sequestration rate})} \) (3.1)

3.4.1 Computing the Environmental Impact Index

Loucks and Gladwell (1999) have presented a method to integrate measures of vulnerability, resilience, and reliability into a single index to evaluate overall sustainability of a water resource system. A similar method has been used by Saling et al. (2002) in the eco-efficiency method to normalize values of energy consumption for the purpose of comparing alternatives. The environmental impact index in this paper is based on the evaluation methods of Loucks and Gladwell (1999) and Saling et al. (2002) and its evaluation is performed in the three steps outlined below.

**Step 1 – Evaluate Measure Indices**

The EIO-LCA model is used to quantify the discharge, consumption, and impact levels of the environmental measures indicated in Table 3.1 for each design alternative. The maximum value of each environmental measure computed across all design alternatives is noted. For each design alternative, the discharge, consumption, and impact levels of all environmental measures in Table 3.1 are divided by their maximum values to create an index that communicates the level of the environmental measure relative to its maximum level

\[
\text{Measure\_Index} = \frac{\text{value of measure for WDS alternative}}{\text{maximum value of measure for all WDS alternatives}}
\] (3.2)

A hypothetical example is used to illustrate the evaluation of the Measure\_Index in Equation 3.2 for sulfur dioxide (SO\(_2\)) emissions. It is assumed that the mass of SO\(_2\) emissions associated with the manufacturing of new pipe and the operation of pumps during the service life of a water
distribution system is computed with an EIO-LCA for 13 design alternatives (Table 3.2). The volume of water delivered to users over the system lifetime is 350,000 ML and the rate of SO$_2$ emission is computed by dividing the mass of SO$_2$ emitted by the volume of water delivered. Table 3.2 indicates that design alternative J has the maximum rate of SO$_2$ emission. The SO$_2$ emission rates of each of the 13 design alternatives are ranked relative to the maximum SO$_2$ emission rate of alternative J with the Measure_Index in Equation 3.2. Applying the Measure_Index in Equation 3.2 to rank the SO$_2$ emission of Alternative A in Table 3.2, we have

$$\text{SO}_2 \text{ Measure_Index for Alternative A} = \frac{2.720 \text{ kg/ML} \times 10^{-6}}{4.601 \text{ kg/ML} \times 10^{-6}} = 0.591$$

The remaining 12 design alternatives are similarly ranked. Design alternative J is given an environmental measure index value of 1 since it produces the highest SO$_2$ emissions in Table 3.2. The Measure_Index in Equation 3.2 can range from 0 to 1. A maximum value of 1 means that a design alternative produces the highest level of discharge, consumption, or impact for an environmental measure (e.g., SO$_2$ emissions) of all the design alternatives considered. Conversely, a minimum value of 0 means that a design alternative produces no discharge, consumption, or impact for an environmental measure. Therefore, the environmental impact of each alternative is always compared with a hypothetical zero-impact alternative.
Table 3.2: Hypothetical example showing values of the SO$_2$ emission measure obtained for 13 WDS design alternatives.

<table>
<thead>
<tr>
<th>Alternative</th>
<th>Mass SO$_2$ (kg)</th>
<th>Mass SO$_2$/Func. Unit (kg/ML)x10$^{-6}$</th>
<th>Measure_Index ($\text{SO}_2$)</th>
<th>Measure_Index Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0.952</td>
<td>2.720</td>
<td>0.591</td>
<td>1</td>
</tr>
<tr>
<td>B</td>
<td>1.014</td>
<td>2.897</td>
<td>0.630</td>
<td>2</td>
</tr>
<tr>
<td>C</td>
<td>1.098</td>
<td>3.137</td>
<td>0.682</td>
<td>3</td>
</tr>
<tr>
<td>D</td>
<td>1.199</td>
<td>3.426</td>
<td>0.745</td>
<td>6</td>
</tr>
<tr>
<td>E</td>
<td>1.442</td>
<td>4.120</td>
<td>0.896</td>
<td>12</td>
</tr>
<tr>
<td>F</td>
<td>1.106</td>
<td>3.159</td>
<td>0.687</td>
<td>4</td>
</tr>
<tr>
<td>G</td>
<td>1.174</td>
<td>3.353</td>
<td>0.729</td>
<td>5</td>
</tr>
<tr>
<td>H</td>
<td>1.261</td>
<td>3.604</td>
<td>0.783</td>
<td>7</td>
</tr>
<tr>
<td>I</td>
<td>1.365</td>
<td>3.900</td>
<td>0.848</td>
<td>10</td>
</tr>
<tr>
<td>J</td>
<td>1.610</td>
<td>4.601</td>
<td>1.000</td>
<td>13</td>
</tr>
<tr>
<td>K</td>
<td>1.265</td>
<td>3.615</td>
<td>0.786</td>
<td>8</td>
</tr>
<tr>
<td>L</td>
<td>1.340</td>
<td>3.829</td>
<td>0.832</td>
<td>9</td>
</tr>
<tr>
<td>M</td>
<td>1.433</td>
<td>4.095</td>
<td>0.890</td>
<td>11</td>
</tr>
</tbody>
</table>

Step 2 – Average Measure Indices by Category

Once index values have been computed for all environmental measures in Table 3.1 with Equation 3.2, they are averaged within each environmental category listed in Table 3.1 to compute an average index value for each environmental category such that

$$\text{Category_Index} = \frac{\sum_{i=1}^{n} \text{Measure_Index}_i}{n}$$

(3.3)

where Category_Index = environmental category index; $n$ = number of environmental measures in an environmental category; Measure_Index$_i$ = Measure_Index value of $i$th measure in an environmental category. Measure indices within a single category are averaged together, as in Equation 3.3, to ensure that categories with multiple measures (e.g., air pollution, non-renewable energy depletion) are given equal weighting as those categories with only a single measure (e.g., fossil-fuel footprint). As will be discussed below, additional weights are applied to the environmental category indices to reflect their relative priority to stakeholders. The computation of an environmental category index for the air pollution category in a design alternative is
illustrated in Table 3.3. Suppose that for a hypothetical design alternative, index values have been computed for the 6 measures of SO$_2$, carbon monoxide, nitrous oxides, volatile organic compounds (VOC), lead and particulate matter emissions in Table 3.1. The air pollution category index is calculated with Equation 3.3 by averaging the index of the 6 air pollution measures in Table 3.3.

**Table 3.3:** Hypothetical example showing how the environmental impact index (EI) is calculated for a particular WDS alternative.

<table>
<thead>
<tr>
<th>Environmental Category</th>
<th>Environmental Measure</th>
<th>Measure Index</th>
<th>Category Index</th>
<th>EI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Air pollution</td>
<td>Sulfur dioxide</td>
<td>0.591</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Carbon monoxide</td>
<td>0.559</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Nitrous oxides</td>
<td>0.590</td>
<td></td>
<td>0.479</td>
</tr>
<tr>
<td></td>
<td>Volatile organic compounds</td>
<td>0.545</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Lead</td>
<td>0.000</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Particulate matter</td>
<td>0.587</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Non-renewable energy depletion</td>
<td>Coal</td>
<td>0.591</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Natural gas</td>
<td>0.586</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Liquefied Natural gas</td>
<td>0.529</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Motor gasoline</td>
<td>0.542</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Distillate</td>
<td>0.568</td>
<td></td>
<td>0.495</td>
</tr>
<tr>
<td></td>
<td>Kerosene</td>
<td>0.000</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Jet fuel</td>
<td>0.555</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Residual</td>
<td>0.590</td>
<td></td>
<td>0.522</td>
</tr>
<tr>
<td>Fossil fuel footprint</td>
<td>Ecological footprint</td>
<td>0.590</td>
<td></td>
<td>0.590</td>
</tr>
<tr>
<td>Toxic releases</td>
<td>Total air releases</td>
<td>0.587</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Water releases</td>
<td>0.540</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Land releases</td>
<td>0.579</td>
<td></td>
<td>0.525</td>
</tr>
<tr>
<td></td>
<td>Underground releases</td>
<td>0.358</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Total transfers</td>
<td>0.563</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Step 3 – Evaluate Overall Environmental Impact Index**

An overall environmental impact index can be calculated by weighting and averaging the $m$ environmental category index values (air pollution, non-renewable energy depletion, fossil-fuel footprint, and toxic releases) as follows.
where $EI = \text{environmental impact index for a WDS alternative}; m = \text{number of environmental category indices}; W_j = \text{stakeholder weight for category } j; \text{Category}_Index_j = \text{Category}_Index value for category } j$. The computation of the environmental impact index for a single design alternative is illustrated in Table 3.3. The environmental impact index is found by averaging the 4 environmental category indices in Table 3.3 with Equation 3.4 using a weight of 1 for each category. The use of unequal category weights signifies that a water utility attributes more importance to some environmental categories than others.

The environmental measures are compartmentalized into environmental policy-related categories, such as non-renewable resource use and fossil fuel emissions. The grouping of measures into categories facilitates non-technical stakeholder participation in the optimization process. These stakeholders may not perform the calculations to size and locate system components but they can relay their policy priorities through the weighting of category indices. For example, if a water utility deems its fossil fuel footprint category index to be more significant than the other four category indices, it may choose to apply a greater weight to the fossil fuel footprint category index. In addition, stakeholders can create more categories from existing or additional measures if desired. Weighting is not applied to individual environmental measures because of the difficulty in prioritizing a large number of environmental measures in a practical design situation. In addition, the unequal number of environmental measures in each environmental category further complicates the assignment of weights to individual measures (Esty et al. 2005).

### 3.5 Environmental Impact Index in Multi-Objective Optimization

The goal of water distribution network design is to size and locate components such as pipes, pumps, and tanks in a network to meet present and future demands and provide acceptable pressures and water quality to users. The system costs include the initial investment of pipes, pumps, and tanks, and the continuing energy costs to pump water in the system. In this paper, the design problem is formulated within a multi-objective optimization framework whereby system costs and environmental impact are minimized simultaneously.
Minimize:

\[ COF = CC + EC \] \hspace{1cm} (3.5) 

\[ EOF = EI \] \hspace{1cm} (3.6) 

where \( COF \) = cost objective function; \( CC \) = present value cost of pipes, pumps, and tanks; \( EC \) = present value energy cost for pumping; and \( EOF \) = environmental objective function; \( EI \) = environmental impact index. The two parts of the cost objective function in Equation 3.5 are expanded to describe the capital cost of pipes, pumps, and tanks, and energy cost for pumping

\[ CC = \sum_{m=1}^{PP} P(D_m, L_m) + \sum_{n=1}^{PMP} PU(HP_n, QP_n) + \sum_{o=1}^{TNK} TK(TD_o, EL_o) \] \hspace{1cm} (3.7)

\[ EC = \sum_{n=1}^{PMP} \sum_{t=1}^{T} K_t E_{n,t} \] \hspace{1cm} (3.8)

where \( PP \) = number of pipes in a network; \( P(D_m, L_m) \) = cost of pipe \( m \) with diameter \( D_m \), and length \( L_m \); \( PMP \) = number of pumps in a network; \( PU(HP_n, QP_n) \) = cost of pump \( n \) with design pumping head \( HP_n \) and design flow rate \( QP_n \); \( TNK \) = number of tanks in a network; \( TK(TD_o, EL_o) \) = cost of tank \( o \) with diameter \( TD_o \) and bottom elevation \( EL_o \); \( K_t \) = present value discounted electricity tariff in year \( t \) ($/kWh); \( E_{n,t} \) = electricity consumption of pump \( n \) in year \( t \) (kWh); \( T \) = number of years in design horizon. The decision variables in the cost objective function (Equation 3.5) can include diameters for new pipes, pump sizes and locations, tank diameters, tank elevations, and tank locations. On/off pump-switching controls can also be selected for a 24-h operation cycle. The cost and environmental objective functions are constrained by the continuity, energy conservation, performance, and design constraints below

Subject to:

(continuity) \[ \sum Q_{in} - \sum Q_{out} = Q_k, \hspace{1cm} k = 1, 2, ..., NN \] \hspace{1cm} (3.9)

(energy conservation) \[ \sum h_f - \sum E_p = 0, \hspace{1cm} \text{for all loops} \] \hspace{1cm} (3.10)

(performance) \[ x_{\text{min}} \leq x \leq x_{\text{max}} \] \hspace{1cm} (3.11)

(design) \[ y_{\text{min}} \leq y \leq y_{\text{max}} \] \hspace{1cm} (3.12)
The constraint in Equation 3.9 ensures that continuity is satisfied at all network nodes. Here, \( NN \) = number of nodes; \( Q_{in} \) = pipe flow into node \( k \); \( Q_{out} \) = pipe flow out of node \( k \); and \( Q_{k} \) = external demand at node \( k \). External demand is the flow of water required by one or many network users (residential, industrial, commercial or a combination of these) at a network node to carry out their daily activities.

The constraint in Equation 3.10 ensures that energy is conserved around all network loops. Here \( h_f \) = headloss across a pipe; and \( E_p \) = energy added to the water by a pump. A network solver that is external to the optimization program usually satisfies both the continuity and energy conservation constraints.

The performance constraints in Equation 3.11 place lower and upper bounds on pipe velocity (to prevent scouring and deposition), on pressure head at nodes, on disinfectant concentrations at nodes, on tanks levels, and on pump-switching operations, etc. to ensure durability, acceptable service, and operational safety. Here \( y \) = vector of parameters to be constrained (e.g., pipe velocity, pressure head, disinfectant concentrations, etc); \( y_{min} \) = vector of lower parameter bounds; \( y_{max} \) = vector of upper parameter bounds.

The design constraints in Equation 3.12 are set by the size and type availability on some decisions variables (e.g., pipes, pumps, and tanks) in the multi-objective optimization. This ensures that the multi-objective optimization program chooses from a set of discrete pipe diameters, pump sizes and models, tank sizes, etc. in the search for the optimal solution. Here \( x \) = vector of decision variables subject to size and type availability; \( x_{min} \) = vector of lower bounds on size and type availability; \( x_{max} \) = vector of upper bounds on size and type availability.

### 3.6 Case Study

The environmental impact index is tested in the design of a water transmission system (Figure 3.1) over a design horizon of 20 years. A 20-year horizon is chosen since it is common in water distribution system design work and because energy price predictions extend no further than 20 years in practice (EIA 2008a). The system is comprised of a water source, a pumping station, a storage reservoir for pressure equalization during peak demand periods, and four transmission mains. The pumping head at the source/pumping station \( (h_p) \) is fixed at 110 m with variable-
speed drives. The storage reservoir has a bottom elevation \((h_r)\) of 97 m, an initial level of 10 m, a minimum level of 1 m, a maximum level of 15 m, and a cross sectional area of approximately 3,848 m\(^2\). The elevation of the demand node is 0 m. The average daily demand at the node is 0.590 m\(^3\)/s. All four PVC mains are 1,000 m in length with a Hazen-Williams ‘C’ factor of 120. To further simplify the analysis, Mains 1 and 2 have equal diameters \((D_1 = D_2)\) and Mains 3 and 4 also have equal diameters \((D_3 = D_4)\). Commercially available PVC nominal pipe diameters 350, 400, 450, 500, and 600 mm are considered in the analysis. Thus, there are 25 \((5^2)\) possible pipe-size alternatives for the transmission system depicted in Figure 3.1. Enumeration rather than the multi-objective optimization program in Equations 3.5 to 3.12 was used to solve the transmission system problem. For simplicity, this case study only considers environmental impacts linked to pipe manufacturing and the lifetime operation of the pumps in the system. Environmental impacts linked to the disposal stage are not considered.

![Figure 3.1: Layout of test system.](image)

### 3.6.1 Functional Unit – Volume of Water Delivered

In this paper, the functional unit is the total volume of water delivered to system users over the 20-year period. It is computed by multiplying the average day demand of 0.590 m\(^3\)/s by 20 years to give a volume of 372 GL (gigalitres).
3.6.2 Pipe Costs and Impacts

Pipe cost is determined by multiplying the unit cost of a pipe, provided by a PVC pipe manufacturer, by its length. The unit cost of commercially-available pipe diameters indicated in Table 3.4 were obtained from a local PVC pipe manufacturer. The environmental measures of pipe fabrication are assessed with the EIO-LCA model produced by the Carnegie Mellon University Green Design Institute (Carnegie 2008). This is performed in two steps. First, since the EIO-LCA incorporates the 1997 Department of Commerce (DOC) Purchaser Price input-output table, the cost of the 4 PVC pipes is discounted to 1997 dollars with an assumed discount rate of 5%. Second, the discounted pipe cost is input into the EIO-LCA model under the industry sector #326122 “Plastics Pipe and Pipe Fitting Manufacturing” to evaluate the environmental measures listed in Table 3.1 for all system alternatives. For example, for SO$_2$, this means using the EIO-LCA model to compute the total mass of SO$_2$ produced in the manufacturing of pipe and dividing that SO$_2$ mass by the volume of water delivered to users throughout the 20-year service life of the system.

Table 3.4: Commercially available nominal and inner pipe diameters.

<table>
<thead>
<tr>
<th>Nominal Diameter (mm)</th>
<th>Inner Diameter (mm)</th>
<th>Unit Cost (US$/m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>350</td>
<td>357.5</td>
<td>103</td>
</tr>
<tr>
<td>400</td>
<td>406.6</td>
<td>134</td>
</tr>
<tr>
<td>450</td>
<td>455.7</td>
<td>170</td>
</tr>
<tr>
<td>500</td>
<td>504.7</td>
<td>210</td>
</tr>
<tr>
<td>600</td>
<td>602.9</td>
<td>300</td>
</tr>
</tbody>
</table>

3.6.3 Pumping Costs and Impacts

Pumping costs are determined by analyzing the system with EPANET2 (Rossman 2000). The 24-h diurnal pattern reported by Buchberger and Li (2007) for Milford, Ohio, indicated in Figure 3.2, is used to model normal water use in the transmission system. Pumping power is estimated in each hour of the 24-h period with the brake horsepower equation

$$bhp = \frac{\gamma Q h}{\eta}$$  \hspace{1cm} (3.13)
where bhp = brake horsepower in kilowatts (kW); \( \gamma \) = unit weight of water at 15 °C of 9.802 kN/m\(^3\); \( Q \) = pump discharge (m\(^3\)/s); \( h \) = pumping head (m) = 110 m; and \( \eta \) = pump efficiency of 85%.

The brake horsepower in Equation 3.13 is integrated over the 24-hour period to calculate the daily pumping energy use and multiplied by 365 days/yr to determine annual energy use. Annual energy use is multiplied by 20 years to compute energy use over the 20–year design horizon. The cost of pumping water over the 20-year design horizon (2008-2028) is based on the United States Annual Energy Outlook 2008, which provides projections of end-use industrial electricity pricing to 2030 (EIA 2008a). Since future electricity pricing is provided in 5-year intervals, yearly prices are linearly interpolated between 5-year intervals. Electricity price projections are provided in 2006 dollars, therefore a future worth calculation with a discount rate of 5% is required to determine the total cost of pumping in 2008 dollars

\[
EC_{2008} = \sum_{n=1}^{PMP} \sum_{t=1}^{T} (K_t E_{n,t}) (1 + r)^2
\]

where \( EC_{2008} \) = total pumping cost in 2008 dollars ($); \( K_t \) = industrial sector electricity tariff in 2006 dollars ($/kWh) in year \( t \); and \( r \) = discount rate = 5%.
The discharge, consumption, and impact levels of the environmental measures in Table 3.1 linked to pumping energy are assessed with the Carnegie Mellon Green Design Institute EIO-LCA online model (Carnegie 2008). First, the daily energy use of pump \( n \) is computed with the brake horsepower equation and multiplied by 365 days/yr to determine the annual energy use of the pump. This value is multiplied by 20 years to obtain the total energy consumed by pump \( n \) over the 20-year design horizon \( (E_{n,20}) \). The 1997 end-use price of $0.0685/kWh (in 1997 dollars) of energy averaged for all sectors is obtained from the United States Electric Power Monthly (EIA 2008b). This end-use price is multiplied by the total energy utilized by pump \( n \) over the 20-year design horizon. Total pumping cost in 1997 dollars is computed by summing energy use across all \( n = 1, 2, 3, \ldots, PMP \) pumps

\[
EC_{1997} = \sum_{n=1}^{PMP} K_{1997} E_{n,20}
\]  

(15)
where $EC_{1997}$ = total pumping cost in 1997 dollars ($); $E_{n,20}$ = total energy use of pump $n$ over 20-year design horizon (kWh); and $K_{1997}$ = average sector electricity tariff in 1997 dollars ($/kWh). The 1997-dollar value for the system is required since the EIO-LCA model uses the 1997 DOC Purchaser Price input-output tables. The total pumping cost in 1997 dollars is input into the EIO-LCA model under the industry sector #2211 “Electric Power Generation, Transmission, and Distribution” to compute the discharge, consumption, and impact levels of each environmental measure in Table 3.1 for each system alternative. For example, for SO$_2$ emissions, this means using the EIO-LCA model to compute the total mass of SO$_2$ produced when operating the pump over the 20-year service life and dividing that SO$_2$ mass by the volume of water delivered to users throughout the 20-year service life of the system.

Three main assumptions are made in using the EIO-LCA to determine the environmental measures associated with the production of electricity for pumping. The first assumption is that the year-over-year energy use for pumping is determined with a single 24-h diurnal demand curve and is thus constant over the 20–year period. The second assumption is that technology and the economic production system in the US are unchanging in time so that the environmental impacts linked to electricity production in 1997 are the same as those linked to electricity production in 2008. The third assumption is that the EIO-LCA provides environmental measures based on the average purchaser price of electric power of all sectors (industrial, commercial, and residential) rather than the industrial price normally paid for energy by a water utility.

### 3.6.4 Total Cost, Total Impacts, and Environmental Impact Index

The total cost of each alternative over the 20-year period is obtained by adding the pipe cost to the net present value of pumping costs in Equation 3.5. The discharge, consumption, and impact levels of each environmental measure in Table 3.1, computed with the EIO-LCA model for pipe manufacturing and pumping energy, are added together for each alternative. An environmental impact index value is calculated for each alternative using Equations 3.2 to 3.4 with equivalent environmental category index weights of 1.

### 3.6.5 Minimum Pressure Head

The EPANET2 model is used to analyze the system under two additional demand scenarios of maximum hourly demand (MHD) and maximum day demand (MDD) plus fire. The MHD
peaking factor is set to 2.0, and the MDD peaking factor is set to 1.7 with a fire flow of 1.0 m³/s (MDD + fire). The lowest pressure head observed at the node in the two peak-demand scenarios is recorded as $h_{sys}$ for that alternative in Table 3.5. An alternative is considered to be hydraulically feasible if $h_{sys}$ at the demand node is greater than or equal to a minimum pressure head of 50 m, thereby ensuring that under a worst-case peak-demand scenario, the system will be able to provide adequate pressure to users. Minimum and maximum pipe velocity bounds and disinfectant concentrations can also be considered in design.

**Table 3.5**: All design alternatives and associated design diameters, pipe cost, pump cost, total cost, cost ranking, pressure head during peak demands, environmental impact index, and environmental ranking.

<table>
<thead>
<tr>
<th>Alt. (D1,D2 D3,D4)</th>
<th>Pipe Cost ($)</th>
<th>Pumping Cost ($)</th>
<th>Total Cost ($)</th>
<th>Cost Rank</th>
<th>$h_{sys}$ (m)</th>
<th>$h_{sys} \geq 50$ (m)</th>
<th>$EI$</th>
<th>$EI$ Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 350,350</td>
<td>412,000</td>
<td>5,436,040</td>
<td>5,848,040</td>
<td>5</td>
<td>41.37</td>
<td>no</td>
<td>0.532</td>
<td>5</td>
</tr>
<tr>
<td>2 350,400</td>
<td>474,000</td>
<td>5,033,932</td>
<td>5,507,932</td>
<td>4</td>
<td>58.32</td>
<td>yes</td>
<td>0.498</td>
<td>4</td>
</tr>
<tr>
<td>3 350,450</td>
<td>546,000</td>
<td>4,745,496</td>
<td>5,291,496</td>
<td>3</td>
<td>70.38</td>
<td>yes</td>
<td>0.475</td>
<td>3</td>
</tr>
<tr>
<td>4 350,500</td>
<td>626,000</td>
<td>4,546,582</td>
<td>5,172,582</td>
<td>2</td>
<td>78.73</td>
<td>yes</td>
<td>0.461</td>
<td>2</td>
</tr>
<tr>
<td>5 350,600</td>
<td>806,000</td>
<td>4,320,556</td>
<td>5,126,556</td>
<td>1</td>
<td>88.41</td>
<td>yes</td>
<td>0.451</td>
<td>1</td>
</tr>
<tr>
<td>6 400,350</td>
<td>474,000</td>
<td>6,414,720</td>
<td>6,888,720</td>
<td>10</td>
<td>60.33</td>
<td>yes</td>
<td>0.626</td>
<td>10</td>
</tr>
<tr>
<td>7 400,400</td>
<td>536,000</td>
<td>6,100,227</td>
<td>6,636,227</td>
<td>9</td>
<td>70.36</td>
<td>yes</td>
<td>0.601</td>
<td>9</td>
</tr>
<tr>
<td>8 400,450</td>
<td>608,000</td>
<td>5,868,037</td>
<td>6,476,037</td>
<td>8</td>
<td>78.01</td>
<td>yes</td>
<td>0.583</td>
<td>8</td>
</tr>
<tr>
<td>9 400,500</td>
<td>688,000</td>
<td>5,704,457</td>
<td>6,392,457</td>
<td>7</td>
<td>83.63</td>
<td>yes</td>
<td>0.573</td>
<td>7</td>
</tr>
<tr>
<td>10 400,550</td>
<td>686,000</td>
<td>5,514,647</td>
<td>6,328,647</td>
<td>6</td>
<td>90.56</td>
<td>yes</td>
<td>0.566</td>
<td>6</td>
</tr>
<tr>
<td>11 450,350</td>
<td>546,000</td>
<td>7,261,410</td>
<td>8,007,410</td>
<td>15</td>
<td>74.06</td>
<td>yes</td>
<td>0.710</td>
<td>15</td>
</tr>
<tr>
<td>12 450,400</td>
<td>608,000</td>
<td>7,053,942</td>
<td>7,661,942</td>
<td>14</td>
<td>79.78</td>
<td>yes</td>
<td>0.694</td>
<td>14</td>
</tr>
<tr>
<td>13 450,450</td>
<td>680,000</td>
<td>6,900,406</td>
<td>7,580,406</td>
<td>12</td>
<td>84.4</td>
<td>yes</td>
<td>0.684</td>
<td>13</td>
</tr>
<tr>
<td>14 450,500</td>
<td>760,000</td>
<td>6,791,461</td>
<td>7,551,461</td>
<td>11</td>
<td>87.98</td>
<td>yes</td>
<td>0.678</td>
<td>12</td>
</tr>
<tr>
<td>15 450,550</td>
<td>940,000</td>
<td>6,663,372</td>
<td>7,603,372</td>
<td>13</td>
<td>92.62</td>
<td>yes</td>
<td>0.677</td>
<td>11</td>
</tr>
<tr>
<td>16 500,350</td>
<td>626,000</td>
<td>7,974,366</td>
<td>8,600,366</td>
<td>19</td>
<td>83.76</td>
<td>yes</td>
<td>0.781</td>
<td>20</td>
</tr>
<tr>
<td>17 500,400</td>
<td>688,000</td>
<td>7,874,278</td>
<td>8,562,278</td>
<td>17</td>
<td>86.88</td>
<td>yes</td>
<td>0.775</td>
<td>18</td>
</tr>
<tr>
<td>18 500,450</td>
<td>760,000</td>
<td>7,800,689</td>
<td>8,560,689</td>
<td>16</td>
<td>89.52</td>
<td>yes</td>
<td>0.773</td>
<td>17</td>
</tr>
<tr>
<td>19 500,500</td>
<td>840,000</td>
<td>7,748,503</td>
<td>8,588,503</td>
<td>18</td>
<td>91.63</td>
<td>yes</td>
<td>0.772</td>
<td>16</td>
</tr>
<tr>
<td>20 500,600</td>
<td>1,020,000</td>
<td>7,686,622</td>
<td>8,706,622</td>
<td>20</td>
<td>97.84</td>
<td>yes</td>
<td>0.777</td>
<td>19</td>
</tr>
<tr>
<td>21 600,350</td>
<td>806,000</td>
<td>9,097,407</td>
<td>9,903,407</td>
<td>21</td>
<td>95.23</td>
<td>yes</td>
<td>0.896</td>
<td>21</td>
</tr>
<tr>
<td>22 600,400</td>
<td>868,000</td>
<td>9,129,711</td>
<td>9,997,711</td>
<td>22</td>
<td>95.85</td>
<td>yes</td>
<td>0.903</td>
<td>22</td>
</tr>
<tr>
<td>23 600,450</td>
<td>940,000</td>
<td>9,150,361</td>
<td>10,090,361</td>
<td>23</td>
<td>96.38</td>
<td>yes</td>
<td>0.909</td>
<td>23</td>
</tr>
<tr>
<td>24 600,500</td>
<td>1,020,000</td>
<td>9,163,649</td>
<td>10,183,649</td>
<td>24</td>
<td>96.8</td>
<td>yes</td>
<td>0.915</td>
<td>24</td>
</tr>
<tr>
<td>25 600,600</td>
<td>1,200,000</td>
<td>9,178,113</td>
<td>10,378,113</td>
<td>25</td>
<td>97.36</td>
<td>yes</td>
<td>0.927</td>
<td>25</td>
</tr>
</tbody>
</table>
3.6.6 Results

For each design alternative, the pipe diameters, pipe cost, pumping cost, total cost, cost rank, pressure head under peak demands, status (pass or fail) of pressure head, environmental impact index, and environmental rank are indicated in Table 3.5. Alternative 1 provides a pressure head below 50 m at the node under MDD + fire demand scenarios and is therefore a hydraulically infeasible alternative. Alternative 5 has the lowest total cost and the lowest environment impact index value of all the hydraulically feasible alternatives. Alternatives 2, 3, 4, 5, and 10 are the five most cost-effective, hydraulically feasible alternatives. These five alternatives also have the lowest environmental impact index values of all hydraulically feasible alternatives.

The environmental impact index is compared with total cost (denoted by the letter “T”) and pumping cost in Figure 3.3 for all hydraulically feasible alternatives. In Figure 3.4, the environmental impact index is compared with pipe cost for all hydraulically feasible alternatives.

In Figures 3.3 and 3.4, the identification number of each design alternative is located next to its corresponding data point. When comparing the cost scales of Figures 3.3 and 3.4, it is evident that pumping cost is much greater than pipe cost for all hydraulically feasible alternatives. The monotonic increasing relationship between EI and cost in Figure 3.4 indicates that cost and environmental performance are closely linked with pumping activity. An increase in electricity consumption for pumping causes a direct increase in pumping cost and in the value of environmental measures and the environmental impact index.
Figure 3.3: Comparison of total cost (T) and pumping cost with environmental impact index for the hydraulically feasible design alternatives.
Figure 3.3 indicates the pumping cost and environmental impact index of all 25 alternatives. This figure clearly shows the importance of pipe diameter selection on pumping cost and environmental impact. When D1/D2 is increased and D3/D4 is held constant, pumping cost increases. This is shown in Figure 3.3 when comparing Alternative 5 (D1/D2 = 350 mm, D3/D4 = 600 mm) and Alternative 10 (D1/D2 = 400 mm, D3/D4 = 600 mm). The reason for the increase in pumping energy with increasing D1/D2 is associated with the filling of the storage tank during off-peak times. For all 25 alternatives, the period of time from hour 2 to hour 6 is associated with the filling of the storage tank. During this time, the system attempts to fill the tank to prepare for the expected increase in demand after this period, as shown in Figure 3.2. When Mains 1 and 2 are larger in diameter, they have a greater cross-sectional area that permits greater flow to the storage tank during off-peak tank-filling times. More water can be stored in the tank with larger Main 1 and 2 diameters, which means less water must be pumped from the source to meet
demand during morning peak conditions. However, in order to get the water to the storage reservoir, the pump must force the water over the full length of the transmission line against higher pressures caused by high water levels in the storage reservoir. Therefore, including larger diameter pipes for Mains 1 and 2 increases pumping energy during tank filling in off-peak demand conditions.

Figure 3.3 also indicates that increasing the diameter of D3/D4 while holding the diameter of D1/D2 fixed produces only marginal reductions in pumping cost and environmental impact index. This is shown in Figure 3.3 with Alternatives 6 through 10, for which D1/D2 is held at 400 mm and D3/D4 increases with increasing alternative number. The percent difference in pumping cost between Alternatives 6 and 10 is 15% even though the percent difference in environmental impact index between the two alternatives is only 10%. This relationship is expected since increases in pipe diameters for D3/D4 result in lower headlosses between the demand node and the storage tank, which in turn lowers pumping costs. Lower pumping costs lead to lower environmental impacts and lower environmental impact index values.

As the D1/D2 diameters are increased in Figure 3.3 and Table 5.5, pumping cost becomes less sensitive to increases in D3/D4. For example, the small-diameter Alternatives 1 through 5 exhibit a larger variation in pumping cost than the large-diameter Alternatives 16 through 20 as D3/D4 diameters are increased. This is because in the small-diameter systems, an increase in D3/D4 diameters produces a significant decrease in headloss between the demand node and the tank, which in turn increases tank draining and lowers the water elevation in the tank. By increasing the D3/D4 diameters in the small-diameter systems, less water must be pumped to the tank against a lower water elevation and this produces a significant decrease in pumping cost. Conversely, in the large-diameter systems with large hydraulic capacity provided by the two mains between the pumping station and the demand node, increasing D3/D4 does not significantly change draining/filling patterns nor does it significantly change the water elevation in the tank. This means that increasing D3/D4 diameters does not significantly change the volume of water pumped to the tank nor does it significantly change pumping costs. It is noted that when D1/D2 values reach 600 mm for Alternatives 21 through 25, an increase in D3/D4 results in an increase in pumping cost. For these Alternatives, increasing pipe diameters D3/D4
further encourages tank filling during hours 2 to 6, which leads to larger flows, higher frictional losses, and higher pumping costs during the off-peak hours.

Figure 3.5 shows the average proportional contribution of pumping energy and pipe fabrication to the value of each environmental measure for all 25 alternatives. As shown in Figure 3.5, pumping energy contributes significantly to the value of most environmental measures comprising the environmental impact index. Pipe fabrication makes a significant contribution to the environmental measures of air emissions of lead and kerosene use as well as to underground releases. Lead and kerosene are not used in pipe manufacturing or electricity production and they therefore make an equal contribution (zero) to these two measures. Underground releases for pipe manufacturing are 13 times higher than for electricity production for pumping per dollar spent, and may involve the injection of toxic fluids into the ground at high pressures to extract the natural gas needed in PVC production (Mall et al. 2007).
The ecological footprint (EF) measure in Table 3.1 provides a conceptual index of the environmental impact of greenhouse gas emissions generated in the fabrication and operation of the system. Alternatives 4 and 5 have volumetric EFs of 12.0 m²/ML (115 kg CO₂/ML emitted) and 15.9 m²/ML (121 kg CO₂/ML emitted), respectively. When applied over the lifetime of both systems, Alternative 4 will require approximately 261 less American football fields of biopductive forest covered land to absorb its resulting lifetime greenhouse gas emissions than Alternative 5. This amounts to approximately 2,232 more metric tons of CO₂ emissions for Alternative 4 over 20 years.

3.7 Broader Implications

In terms of the system analyzed, the method used here to assess the environmental impact of a WDS alternative shows the relationship between pipe cost, pumping cost, and system environmental impact. In this system, the relationship between pumping energy and environmental impact is stronger than the relationship between pipe manufacturing and environmental impact. However, pipe selection significantly affects the overall environmental impact index of the system insofar as it influences pumping energy requirements in a system and has the potential to influence total cost ranking between alternatives with similar pumping costs. In a system where pipes are more numerous and more storage reservoirs exist, the interplay between pipe cost, pumping cost and environmental impact may be more or less sensitive to small changes in pipe diameter. It is evident that pumps and storage reservoirs and their associated capacities and locations with respect to the source can have major impact on overall cost and environmental impact.

The Carnegie Mellon EIO-LCA model was used to determine the impact, discharge, and consumption measures associated with the test system due to its accessibility, ease of use, and its high level of disaggregation (519 sectors). Uncertainties in the analysis stem from missing, outdated, and aggregated data in the Carnegie Mellon EIO-LCA (Carnegie 2008). A more in-depth analysis and reworking of the major environmental policy issues surrounding municipal water distribution systems should be conducted to allow for the insertion, deletion, and consolidation of environmental categories as well as environmental impact, consumption, and discharge measures for the model. In addition, updated adjustments to the EIO-LCA measure values and additional methods of obtaining environmental measures should be explored. This
study did not include an analysis of the sensitivity of the environmental impact index ranking to uncertain variables such as discount rate, and weighting of category indices. In addition, a method for choosing weights for the category indices was not provided and various weighting methods should be investigated and the sensitivity of the model to each should be analyzed. Analyzing the sensitivity of the environmental impact index to these factors in a larger and more complex system will provide more information on the significance of variations in cost and environmental index values between solutions, which will be valuable in decision-making for stakeholders.

3.8 Summary and Conclusions

This paper presented a new index for evaluating the environmental impact of a water distribution network. The new environmental impact index evaluates the environmental effect of a network in relation to resource consumption (non-renewable energy use), environmental discharges (air pollutants, toxic releases to air, water, and land), and environmental impacts (ecological fossil-fuel footprint) associated with pipe fabrication and pumping of water. After aggregation, the index was used to rank the environmental impact of a network alternative relative to other network alternatives in water distribution network design. The environmental impact index can be incorporated into multi-objective optimization to identify alternatives that minimize cost and minimize environmental impacts and that satisfy performance and design constraints.

The index was applied to a simple pump-pipe transmission system over a planning period of 20 years and all cost and environmental measures associated with pipe fabrication and pumping water were considered. For the system analyzed, pumping cost had a significant influence over total cost, environmental impact, and the majority of individual environmental measures. While pipe selection had a small, direct influence over system cost and environmental impact, its control of pumping energy requirements had a large, indirect influence over system cost and environmental impact. While the method was applied to a simple system in this paper, in the future the method will be applied to more complex systems to further understand the relationship between system environmental impact and system cost.
3.9 References


58


Chapter 4
Evaluating the Environmental Impacts of Water Distribution Systems Using EIO-LCA-Based Multi-Objective Optimization

In Chapter 3, environmental impacts were considered in the design of a water transmission system by means of the environmental impact (EI) index developed in this thesis. In Chapter 4, the EI index is combined with the non-dominated sorting genetic algorithm-II (NSGA-II) multi-objective optimization. The multi-objective optimization approach includes the EI index as an objective along with capital cost and annual pumping energy use as additional objectives. The new optimization approach is applied to the benchmark “Anytown” WDS expansion problem to demonstrate its viability as a decision-making tool and to investigate how the EI index ultimately affects Pareto-optimal solutions in WDS expansion optimization.

4.1 Abstract
Climate change has made environmental impact a factor of growing importance in decision-making for municipalities. Increasingly, environmental impacts of expanding and operating a water distribution system (WDS) are being considered alongside cost and hydraulic design. The paper presents a non-dominated sorting genetic algorithm (NSGA-II) that minimizes capital costs, annual pumping energy use, and environmental impacts in WDS design, while adhering to hydraulic constraints. A previously developed environmental impact (EI) index is included in the environmental objective function of the optimization program. The EI index normalizes and aggregates multiple environmental measures evaluated with an economic input-output life cycle assessment (EIO-LCA) model. The EIO-LCA-based NSGA-II was applied to the Anytown network. Preliminary results indicated that solutions obtained with the triple-objective capital cost/energy/EI index optimization minimize a number of environmental impact measures while producing results that are similar in pumping energy use value and, in some instances, slightly higher in capital cost when compared to solutions obtained with a double cost/energy optimization in which environmental impact was excluded. The location and shape of the Pareto fronts were sensitive to demand and ‘C’ factor adjustments with greater sensitivity observed with changes in demand than changes in ‘C’ factor.
4.1.1 Introduction

Traditionally, water network design optimization has focused on minimizing cost while meeting hydraulic and water quality performance. Engineering researchers and practitioners are starting to recognize the need to design networks to make them more compatible with their natural and social environments. The materials used in water network components (e.g., pipes, pumps, and tanks) must be extracted, produced, and manufactured. Pumping water in the operating stage of a network consumes electricity. System components must be disposed of at the end of their service life. These activities consume material and energy resources and generate greenhouse gas (GHG) emissions, air pollution, and solid waste.

The application of life cycle assessment (LCA) to WDS decision-making has been explored in the literature. Dennison et al. (1999) compared the environmental impact of pipe materials using LCA while Lundie et al. (2004, 2005) applied LCA to compare alternatives for wastewater, stormwater, and drinking water. Jeppsson & Hellstrom (2002) combined LCA with Material Flow Analysis (MFA) to track individual mass flows of a given system from material extraction to disposal. Filion et al. (2004) used economic input-output life cycle assessment (EIO-LCA) to quantify energy use in the fabrication stage of a WDS to compare pipe replacement scenarios. Stokes & Horvath (2006) adopted a similar approach to compare the impacts of WDS alternatives designed to address water shortages. Ghimire & Barkdoll (2007) proposed to apply the LCA-based eco-efficiency analysis method to WDS optimization.

Environmental impacts have also been incorporated into WDS optimization. Dandy et al. (2006) were the first to use a single-objective optimization program to minimize the mass, embodied energy, and GHG emissions associated with the manufacturing of network pipes. More recently, Dandy et al. (2008) used the non-dominated sorting genetic algorithm (NSGA-II) to optimize for cost and embodied energy in unplasticised polyvinyl chloride (PVC-U) and modified PVC (PVC-M) pipe material. Wu et al. (2008, 2009) formulated single-objective and multi-objective optimization approaches that considered the cost of GHG emissions in pipe manufacturing and electricity production for pumping. Their approach considered the impact of a range of uncertain discount rates and carbon prices on the capital and operating costs of Pareto-optimal solutions.
More recently, Herstein et al. (2008, 2009) developed an EIO-LCA-based Environmental Impact (EI) index that quantifies environmental impact measures such as air emissions, non-renewable energy resource use, GHG emissions, and other environmental releases. The preliminary studies by Herstein et al. (2008, 2009) indicated that the EI index could be incorporated into a multi-objective WDS optimization program as an objective to be minimized alongside capital and operational costs.

This paper presents an EIO-LCA-based multi-objective NSGA-II that incorporates multiple environmental impact measures on non-renewable energy use, air pollution, and environmental releases into its objective functions. The paper first discusses how environmental impacts are quantified by means of the new EI index developed in Herstein et al. (2008, 2009). Then, the paper describes the structure of the multi-objective WDS expansion optimization problem and how the EI index is incorporated as an objective in this optimization framework. The EIO-LCA-based NSGA-II is then applied to a modified version of the Anytown problem (Walski et al. 1987) to demonstrate how the inclusion of environmental impacts in water distribution expansion optimization can produce practical Pareto-optimal solutions while minimizing environmental impacts.

4.2 Environmental Impact Index

The EI index measures the overall environmental impact of one optimization solution relative to other solutions through the aggregate analysis of a number of environmental measures. This combined index allows decision makers to consider multiple environmental measures in a single environmental objective, which can be optimized alongside additional objectives (e.g., cost). The index value of a solution is determined through a three-step process, which was presented in Herstein et al. (2008, 2009). An abridged version of the three-step process is presented below in the context of a multi-objective genetic algorithm (MOGA)-based optimization.

4.2.1 Environmental Categories and Environmental Measures

The environmental categories and measures used in the analysis of the Anytown system in this paper are listed in Table 4.1. All measures listed in Table 4.1, are from the Carnegie Mellon Green Design Institute’s Online EIO-LCA tool (Carnegie 2009) and are organized into environmental categories. The category “Conventional air pollutants with known human health
effects” includes air pollutants monitored by the United States Environmental Protection Agency (USEPA) which are known to cause adverse human health effects mostly relating to respiratory illness (USEPA 2008). The environmental category “Non-renewable energy depletion” includes non-renewable energy sources like coal and natural gas. The “Releases to the environment” category includes global warming potential (consolidated measure of GHG emissions), and environmental measures that the EPA includes in its Toxic Release Inventory (TRI) Program. The TRI reports on the release and disposal of over 650 chemical pollutants (USEPA 2009) and these are consolidated into air, water, land, and underground releases in the EIO-LCA model (Carnegie 2009).

The original grouping of categories and measures in Herstein et al. (2008, 2009) has been changed in table 4.1 to ensure a similar number of measures in each category and thus an approximately equal weighting of each category in the index. This prevents a single measure from dominating the final index value. For example, Herstein et al. (2008, 2009) presented four environmental categories, which contained anywhere from one to nine measures. This meant that the single measure featured in the single-measure category was better represented in the final EI index than a measure in the nine-measure category. Table 4.1 features categories with four to five environmental measures. Global warming potential has been included in the toxic releases to the environment category and a number of individual measures have been consolidated where appropriate. For example, liquefied petroleum gas, distillate fuel, and residual fuel have been combined because all of these fuels are primarily used in boilers and furnaces, and motor and jet fuel have been combined because they are both used in transportation. Land and underground releases have been grouped together, as have publicly owned treatment works (POTW) toxic transfers and offsite toxic transfers. Lead emissions and kerosene depletion have been removed from the index, as the values for these environmental measures for all industry sectors used in the Anytown analysis are approximately equivalent to zero. Therefore, lead and kerosene will each result in a measure index value of zero for any system solution analyzed, making these measures insignificant in the relative EI index analysis of the Anytown system.
Table 4.1: Environmental categories and environmental measures included in the EI index.

<table>
<thead>
<tr>
<th>Environmental Category</th>
<th>Environmental Measure</th>
<th>Type</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conventional air pollutants with known human health effects</td>
<td>Sulfur dioxide discharge</td>
<td>discharge</td>
<td>metric tons (t)</td>
</tr>
<tr>
<td></td>
<td>Carbon monoxide discharge</td>
<td>discharge</td>
<td>t</td>
</tr>
<tr>
<td></td>
<td>Nitrogen oxides discharge</td>
<td>discharge</td>
<td>t</td>
</tr>
<tr>
<td></td>
<td>Volatile organic compounds discharge</td>
<td>discharge</td>
<td>t</td>
</tr>
<tr>
<td></td>
<td>Particulate matter &lt; 10µm discharge</td>
<td>discharge</td>
<td>t</td>
</tr>
<tr>
<td>Non-renewable energy depletion</td>
<td>Coal consumption</td>
<td>consumption</td>
<td>teraJoules (TJ)</td>
</tr>
<tr>
<td></td>
<td>Natural gas consumption</td>
<td>consumption</td>
<td>TJ</td>
</tr>
<tr>
<td></td>
<td>LPG¹, distillate fuel, residual fuel</td>
<td>consumption</td>
<td>TJ</td>
</tr>
<tr>
<td></td>
<td>Motor fuel, Jet fuel consumption</td>
<td>consumption</td>
<td>TJ</td>
</tr>
<tr>
<td>Releases to the environment</td>
<td>Global Warming Potential impact</td>
<td>impact</td>
<td>t of CO₂ equivalents (tCO₂)</td>
</tr>
<tr>
<td></td>
<td>Total air releases discharge</td>
<td>discharge</td>
<td>kilograms (kg)</td>
</tr>
<tr>
<td></td>
<td>Water releases discharge</td>
<td>discharge</td>
<td>kg</td>
</tr>
<tr>
<td></td>
<td>Land and underground releases discharge</td>
<td>discharge</td>
<td>kg</td>
</tr>
<tr>
<td></td>
<td>POTW², offsite transfers discharge</td>
<td>discharge</td>
<td>kg</td>
</tr>
</tbody>
</table>

¹ LPG: Liquefied petroleum gas.
² POTW: publicly owned treatment works

4.2.2 Step 1 – Evaluate Measure Indices for Each Individual

The environmental measure of each population member is evaluated with EIO-LCA and compared with those of other members of the current population and past populations to update the maximum measure value. A population member’s measure index in Equation 4.1 is calculated by dividing the population member’s measure value by the maximum measure value observed across all members in the current population and past populations.

\[
\text{Meas. Index of Member} = \frac{\text{Value of Meas. for Pop. Member}}{\text{Max. Measure Value Observed}}
\]  

(4.1)

4.2.3 Step 2 – Average measure indices by category

The environmental measures in Table 4.1 are grouped into environmental categories which reflect major environmental issues that are important to stakeholders. Once measure indices for each population member have been calculated, they are averaged within impact categories in order to determine the member’s category indices.
\[
\text{Member Category Index} = \frac{\sum_{j=1}^{n} \text{Member's Meas. Index}_j}{n}
\]  
\[\text{(4.2)}\]

where \( n \) = number of environmental measures in a given category.

### 4.2.4 Step 3 – Evaluate EI Index

A member’s EI index is calculated by averaging the category index values of that member. Stakeholder priorities can be reflected in the EI index through the weighting of category index values in the calculation of the EI index

\[
\text{EI Index of member} = \frac{\sum_{j=1}^{m} w_j \ast (\text{Member's Cat. Index } j)}{m}
\]

\[\text{(4.3)}\]

where \( m \) = number of environmental category indices; and \( w \) = weight assigned to environmental category \( j \).

### 4.3 Network Expansion Formulation

The goal of water distribution network design is to size and locate components such as pipes, pumps, and tanks in a network to meet present and future demands and provide acceptable pressures and water quality to users at a reasonable cost. The system costs include the initial capital investment of pipes, pumps, and tanks, and the continuing energy costs to pump water in the system. Environmental impacts linked to the manufacture of pipe, pump, and tank components and the continuing impacts associated with electricity production for pumping water are also included in the multi-objective optimization approach below. In this paper, the design problem is formulated with a multi-objective optimization program whereby three objectives of capital cost, annual pumping energy use (in kWh/year), and environmental impact are simultaneously minimized.
4.3.1 EIO-LCA-Based Multi-Objective Optimization Approach

Minimize:

\[
COF = CC
\] 
(4.4)

\[
NRGOF = \sum_{a=1}^{PMP} \sum_{t=1}^{T} E_{a,t} / T
\] 
(4.5)

\[
EOF = EI
\] 
(4.6)

where \( COF = \) cost objective function ($) ; \( CC = \) capital cost, which includes the present value cost of new pipes and new tanks ($) ; \( NRGOF = \) pumping energy use objective function (kWh/yr) ; \( PMP = \) number of pumps in a network ; \( T = \) number of years in design period ; \( E_{a,t} = \) electricity consumption of pump \( a \) in year \( t \) (kWh) ; \( EOF = \) environmental objective function ; and \( EI = \) environmental impact index.

The cost objective function in Equation 4.4 includes the capital cost of new pipes, pipe cleaning and lining, and new tanks

\[
CC = \sum_{b=1}^{PP1} P(D_b, L_b) + \sum_{c=1}^{PP2} CL(D_c, L_c) + \sum_{d=1}^{TNK} TK(TD_d, EL_d)
\] 
(4.7)

where \( PP1 = \) number of new pipes in a network ; \( P(D_b, L_b) = \) cost of new pipe \( b \) with diameter \( D_b \), and length \( L_b \) ; \( PP2 \) number of pipes that are being cleaned and lined ; \( CL(D_c, L_c) = \) cost of cleaning and lining pipe \( c \) with diameter \( D_c \) and length \( L_c \) ; \( TNK = \) number of tanks in a network ; and \( TK(TD_d, EL_d) = \) cost of tank \( d \) with diameter \( TD_d \) and bottom elevation \( EL_d \). The addition of new pumps and a designed 24-h on/off pump-switching schedule are not included in Equation 4.7 but can be added as decision variables.

Annual pumping energy use (in kWh/year) rather than pumping cost (usual case) is included as an objective in Equation 4.5. Annual pumping energy use has been included as an objective since: 1) there is no need to adopt a net present value discount rate, and this reduces the uncertainty associated with characterizing pumping activities ; 2) minimizing annual pumping energy use will minimize pumping cost.
The cost and environmental objective functions are constrained by the continuity at nodes, energy conservation around network loops, and performance and design constraints.

Subject to:

(continuity at nodes) \[ \sum Q_{in} - \sum Q_{out} = Q_k, \quad k = 1,2,\ldots,NN \] (4.8)

(loop energy conservation) \[ \sum h_f - \sum E_p = 0, \quad \text{for all loops} \] (4.9)

(performance) \[ x_{\text{min}} \leq x \leq x_{\text{max}} \] (4.10)

(design) \[ y_{\text{min}} \leq y \leq y_{\text{max}} \] (4.11)

where \( NN \) = number of nodes; \( Q_{in} \) = pipe flow into node \( k \); \( Q_{out} \) = pipe flow out of node \( k \); and \( Q_k \) = external demand at node \( k \); \( h_f \) = headloss across a pipe; and \( E_p \) = energy added to the water by a pump. The EPANET2 (Rossman 2000) network solver is used to satisfy the continuity and energy conservation constraints.

The performance constraints in Equation 4.10 place lower and upper bounds on pipe velocity (to prevent scouring and deposition), on pressure head at nodes, and on tank levels to ensure durability, acceptable service, and operational safety. Here \( x \) = vector of parameters to be constrained (e.g., pipe velocity, pressure head, tank levels, etc); \( x_{\text{min}} \) = vector of lower parameter bounds; \( x_{\text{max}} \) = vector of upper parameter bounds.

The design constraints in Equation 4.11 are set by the size and type availability on some decisions variables (e.g., pipes and tanks). This ensures that the multi-objective optimization program chooses from a set of discrete pipe diameters and tank sizes. Here \( y \) = vector of decision variables subject to size and type availability; \( y_{\text{min}} \) = vector of lower bounds on size and type availability; \( y_{\text{max}} \) = vector of upper bounds on size and type availability.

4.4 Non-Dominated Sorting Genetic Algorithm-II (NSGA-II)

Genetic algorithms (GA) are based on the natural phenomenon of genetic evolution whereby the GA evolves solutions through computer-simulated versions of genetic selection, crossover, mutation to arrive at the best, or “fittest” solutions. Multi-objective genetic algorithms (MOGA) have been used to balance two or more competing objectives in the WDS expansion problem to
identify an optimal set of “fit” solutions allowing decision-makers to analyze these optimal solutions in a post-optimization process (Srinivas and Deb 1994; Cheung et al. 2003).

Initial MOGA methods applied to WDS optimization by Halhal et al. (1997) and Walters et al. (1999) incorporated the “messy” GA with a cost objective and a benefit objective which considered pressure, maintenance, operational, and water quality issues associated with new, parallel, cleaned and lined pipes, and additional storage and pumping capacity. Wu and Walski (2005) developed an adaptive penalty technique to handle constraints in multi-objective optimization without having to determine penalty factors a priori. Recently, many researchers have implemented the multi-objective non-dominated sorting genetic algorithm-II (NSGA-II) (Deb et al. 2002) in water distribution research due to its simple and effective constraint-handling technique (Farmani et al. 2005b). Other advantages of the NSGA-II include: i) a rapid non-dominated sorting approach, ii) the ability to preserve good solutions throughout the evolution process, and, iii) the lack of a need for the a priori specification of parameters (Deb et al. 2002).

In the past five years, researchers have exploited the simple constraint-handling characteristics of the NSGA-II to tackle the highly non-linear constrained, discrete WDS expansion problem. Formiga et al. (2003) applied the NSGA-II to a WDS expansion study where pipe cost, flow path redundancy, and system demand-supply ratio were included as competing objectives. Farmani et. al (2005a,b) applied the NSGA-II to investigate the relationship between the total present value of system costs (pipes, pumps, tanks, pressure valves) and system reliability, and between total system cost and minimum surplus head violations. In some cases the NSGA-II has been modified and coupled with other optimization techniques to improve its search capability (Nicolini 2005) and to guide WDS expansion toward solutions that are more robust and better able to deal with demand and uncertainty (Kapelan et al. 2006). The NSGA-II has recently been used to incorporate environmental impacts into the multi-objective WDS expansion problem. Previously mentioned works by Wu et al. (2008, 2009) and Dandy et al. (2008) both used the NSGA-II to minimize system costs while minimizing a second environmental impact associated objective. In this paper, The EI index and the NSGA-II model were used to minimize a capital cost objective, a pumping energy objective, and an environmental impact objective in the WDS expansion optimization problem.

68
4.5 Anytown Case Study

The Anytown system of Walski et al. (1987) is indicated in Fig. 4.1. The original Anytown expansion problem was focused on minimizing the cost of upgrading through pipe cleaning and lining of existing pipes, parallel pipe addition, and by adding new pipes, and tanks while meeting minimum pressure requirements under normal and peak demand conditions. In this paper, the multi-objective NSGA-II by Deb et al. (2002) was implemented to solve the Anytown expansion problem by minimizing the capital costs of new and parallel cement-mortar lined ductile iron pipes, cleaning and lining of existing pipes, and adding new tanks. Annual energy use of pumping and environmental impacts evaluated with the EI index were also minimized.
Figure 4.1: Anytown network with new tank at node 175.

4.5.1 Tank Location, Pipe Material, and Environmental Impacts

A new tank at node 175 (Figure 4.1) was selected prior to optimization. This tank location has been chosen in previous Anytown optimization studies (Walski et al. 1987, Farmani et al. 2005b, Walters et al. 1999). Cement-mortar lined ductile iron (DI) material was selected for all new pipes. The case study considered environmental impacts linked to manufacturing of new pipes.
and the new tank, and the annual electricity use for pumping. Environmental impacts linked to pipe cleaning and lining were not considered due to the lack of data.

4.5.2 Chromosome Coding Structure

The NSGA-II algorithm by (Deb et al. 2002) and the implementation code by Illinois Genetic Algorithms Laboratory (Sastry 2007) were used in this case study. Anytown solutions were coded with 78-gene chromosomes indicated in Figure 4.2, where decision variables (genes) are represented by boxes with gene numbers above each box. The number of options (alleles) and option descriptions for each decision variable are provided in Table 4.2.

![Chromosome Coding of Anytown Solutions](image)

**Figure 4.2:** Chromosome coding of Anytown solutions.

<table>
<thead>
<tr>
<th>Decision variable</th>
<th>No. of options</th>
<th>Options</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tank size</td>
<td>6</td>
<td>6 available tank volumes</td>
</tr>
<tr>
<td>Parallel pipes</td>
<td>12</td>
<td>No pipe, 11 available pipe diameters</td>
</tr>
<tr>
<td>New pipes</td>
<td>11</td>
<td>11 available pipe diameters</td>
</tr>
<tr>
<td>Clean and line existing pipes</td>
<td>2</td>
<td>Yes/No</td>
</tr>
</tbody>
</table>

4.5.3 Pipe Costs and Embodied Environmental Impacts of Pipe

Pipe costs are listed in Table 4.3 and were based on 2009 pricing provided by a local cement-mortar lined DI pipe manufacturer. Pipe pricing has been converted from Canadian to US dollars with an average 2009 exchange rate (Bank of Canada 2009) and excludes excavation, pipe laying, bedding, backfill, and restoration costs. Environmental measures for pipe fabrication were evaluated with the EIO-LCA 1997 USA purchaser model (Carnegie 2009) which is based on 1997 purchaser dollars. The United States Bureau of Labor Statistics Producer Price Index (PPI) (USBLS 2009) for the PPI industry sector “Fabricated Iron and Steel Pipe and Pipe Fittings”
(sector # 332996-01) was used to adjust the 2009 cement-mortar lined ductile iron pipe costs (Table 4.3) to 1997 dollars with Equation 4.12

\[
1997 \text{ cost} = (2009 \text{ cost}) \times \left(\frac{1997 \text{ Index value}}{2009 \text{ Index Value}}\right)
\]  

(4.12)

The 1997 cement-mortar lined ductile iron pipe cost was input into 1997 EIO-LCA model (Carnegie 2009) in the EIO-LCA industry sector “Fabricated Pipe and Pipe Fitting Manufacturing” (sector # 332996) to evaluate the environmental measures in Table 4.1.

**Table 4.3:** Cost of new cement-mortar lined ductile iron pipe, and cost of cleaning and lining existing pipe.

<table>
<thead>
<tr>
<th>Nominal Diameter (mm)</th>
<th>New DI Pipe</th>
<th>Cleaning and Lining Existing Pipe</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inner Diameter (mm)</td>
<td>Unit Cost (US $/m)</td>
<td>Cost (US $/m)</td>
</tr>
<tr>
<td>100</td>
<td>115.5</td>
<td>56.35 N/A</td>
</tr>
<tr>
<td>150</td>
<td>168.9</td>
<td>54.48 N/A</td>
</tr>
<tr>
<td>200</td>
<td>223.5</td>
<td>68.07 54.10</td>
</tr>
<tr>
<td>250</td>
<td>275.3</td>
<td>88.17 58.82</td>
</tr>
<tr>
<td>300</td>
<td>328.2</td>
<td>112.51 66.26</td>
</tr>
<tr>
<td>350</td>
<td>380.7</td>
<td>158.25 N/A</td>
</tr>
<tr>
<td>400</td>
<td>433.4</td>
<td>186.33 N/A</td>
</tr>
<tr>
<td>450</td>
<td>486.2</td>
<td>231.71 N/A</td>
</tr>
<tr>
<td>500</td>
<td>538.9</td>
<td>262.42 N/A</td>
</tr>
<tr>
<td>600</td>
<td>644.4</td>
<td>355.24 N/A</td>
</tr>
<tr>
<td>750</td>
<td>800.4</td>
<td>543.15 78.56</td>
</tr>
</tbody>
</table>

N/A: Not applicable – existing pipes with these diameters are not present in the Anytown system.

**4.5.4 Pipe Cleaning Costs**

Pipe cleaning costs were estimated using cleaning and cement-mortar lining costs from Walski (1986) (Table 4.3). As suggested by Walski (1986), the 1984 cast iron pipe cleaning and cement-mortar lining costs were adjusted to 2009 values with the Engineering News Record Construction Cost Index (ENR 2009). Cleaning and lining costs include the cost of labour, materials, equipment, and contractor overhead and profit and exclude the cost of excavation, mobilization, temporary service, or valve replacement (Walski 1986).
4.5.5 Tank Costs and Embodied Environmental Impacts of Tanks

The cost of the new tank 175 connected to node 140 was established with the tank volume and pricing data indicated in Table 4.4 obtained from a US steel water tower supplier. The PPI industry sector “Other Fabricated Structural Metal” (sector # 332312-5) was used to adjust the 2009 tank costs to 1997 tank costs with Equation 4.12. (Note that the PPI does not provide an industry for steel water tower construction. The “Other Fabricated Structural Metal” PPI sector was used to approximate the price change of steel tanks.) The 1997 tank cost was input into 1997 EIO-LCA model (Carnegie 2009) in the EIO-LCA industry sector “Water, sewer, and pipeline construction” (sector # 235910) to evaluate the environmental measures in Table 4.1. (Note that the EIO-LCA model does not include a sector that specifically addresses water tower construction. Further, the 1997 North American Industry Classification System (NAICS), used by the EIO-LCA purchaser model, does not list water tower construction under its “Water, sewer, and pipeline construction” sector but in the 2002 NAICS, this sector does cover water tower construction.)

Table 4.4: Tank volumes and construction costs.

<table>
<thead>
<tr>
<th>Capacity (m³)</th>
<th>Capacity (US gal)</th>
<th>Cost (US $)</th>
</tr>
</thead>
<tbody>
<tr>
<td>189</td>
<td>50,000</td>
<td>540,000</td>
</tr>
<tr>
<td>379</td>
<td>100,000</td>
<td>615,000</td>
</tr>
<tr>
<td>946</td>
<td>250,000</td>
<td>820,000</td>
</tr>
<tr>
<td>1893</td>
<td>500,000</td>
<td>1,120,000</td>
</tr>
<tr>
<td>5678</td>
<td>1,500,000</td>
<td>2,770,000</td>
</tr>
<tr>
<td>7570</td>
<td>2,000,000</td>
<td>3,590,000</td>
</tr>
</tbody>
</table>

4.5.6 Normal-Day Diurnal Demand, Energy Use, and Environmental Impacts of Pumping

Annual pumping energy use was determined with the 1985 and 2005 average day nodal demands and normal-day water use pattern from Walski et al. (1987) and EPANET2 (Rossman 2000). The 20 year design period (1985-2005) was divided into two 10-year demand periods to account for long-term population growth in Anytown. Annual energy use for the first demand period (1985-1995) was estimated with the 1985 average day nodal demands and the normal-day diurnal pattern in Walski et al. (1987). Annual energy use for the second demand period (1995-2005) was estimated with the 2005 average day normal demands and the normal diurnal pattern in
Walski et al. (1987). The annual energy use for the 20-year design period was averaged over the two 10-year demand periods.

Hazen Williams ‘C’ factors of new cement-mortar lined ductile iron pipes were decreased over the two 10-year demand periods to account for pipe roughening and aging in Table 4.5: A manufacturer-specified ‘C’ factor of 140 for new cement-mortar lined ductile iron pipe was applied to the first 10-year demand period. A ‘C’ factor of 130 for cement-mortar lined ductile iron pipes with an approximate age of 20 years from Sanks (2008) was applied to the second 10-year demand period. Existing pipes with age of approximately 60 years were assigned a ‘C’ factor of 120 (specified in Walski et al. 1987) in the first and second 10-year demand periods in Table 4.5. Similarly, existing pipes with age of approximately 100 years (approximately) were assigned a ‘C’ factor of 70 (specified in Walski et al. 1987) in the first and second 10-year demand periods in Table 4.5. Therefore, no decrease in ‘C’-factor over the 20-year design period in existing 60-year and 100-year old pipes was assumed in this study. Cleaned and lined existing pipes were assigned a ‘C’-factor of 125 (specified in Walski et al. 1987) in the first and second 10-year demand periods in Table 4.5.

Environmental impacts of electricity production for pumping were evaluated with the 1997 EIO-LCA model (Carnegie 2009) which is based on 1997 US energy pricing. The total 1997 electricity cost was calculated by multiplying the total energy use over the two 10-year demand periods (described above) by the 1997 US energy price of $0.0685/kWh averaged for residential, commercial, and industrial users (USEIA 2009). The 1997 electricity cost was input into the 1997 EIO-LCA model (Carnegie 2009) under the sector “Electric Power Generation” (sector # 22111) to calculate the environmental measures in Table 4.1.

**Table 4.5:** Pipe Hazen Williams ‘C’-factors in the first and second 10-year demand periods in Anytown.

<table>
<thead>
<tr>
<th>Pipe material</th>
<th>‘C’-factor (first 10-year period)</th>
<th>‘C’-factor (second 10-year period)</th>
</tr>
</thead>
<tbody>
<tr>
<td>New cement-mortar lined DI pipe</td>
<td>140</td>
<td>130</td>
</tr>
<tr>
<td>Ex. unlined pipes (60 years)</td>
<td>120</td>
<td>120</td>
</tr>
<tr>
<td>Ex. unlined pipes (100 years)</td>
<td>70</td>
<td>70</td>
</tr>
<tr>
<td>Cleaned and lined pipes</td>
<td>125</td>
<td>125</td>
</tr>
</tbody>
</table>
4.5.7 Total Cost, Total Environmental Impacts, and EI Index

The 2009 capital cost was calculated by adding the new pipe cost, the cleaning and lining cost, and the tank cost of each solution. The environmental measure values in Table 4.1 associated with pipe manufacturing, tank construction, and pumping energy were added together in each solution. An environmental impact index was calculated for each solution using Equations 4.1 to 4.3 with environmental category weights of 1.

4.5.8 Peak Demand Conditions and Performance Constraints

In addition to normal-day diurnal demand, maximum hour demand (MHD) and maximum day demand (MDD) plus fire conditions were considered in the Anytown problem. The MHD peaking factor was set to 1.8, and the MDD peaking factor was set to 1.3 with a required fire flow of 32 L/s for all nodes with the exception of node 90 (158 L/s), nodes 75, 115, and 55 (95 L/s), and nodes 120 and 160 (63 L/s). A minimum allowable pressure of 28 m H₂O was adopted at all nodes for MHD, and a minimum allowable pressure of 14 m H₂O for MDD + fire.

Significant increases in pipe velocity can cause pipe scouring. To prevent this, a maximum pipe velocity constraint of 3 m/s (Walski et al. 2001) was adopted for all demand conditions. The minimum pressure and maximum velocity constraints were handled within the NSGA-II through a constrained tournament selection method outlined by Deb et al. (2002).

4.6 Results and Discussion

4.6.1 Pareto-Front Analysis

The Pareto front obtained in the triple-objective optimization of capital cost, annual pumping energy use, and the EI index is indicated in Figures 4.3a-c. Figure 4.3a indicates that capital cost and the EI index have an inverse relationship while Figure 4.3b suggests that annual pumping energy use and the EI index exhibit a linear relationship (or nearly so). These relationships are not as well defined at low and high values of capital cost and energy use, where the EI index values remain relatively constant. The solutions labeled “Pareto front with EI objective” in Figure 4.3c indicate that capital cost and annual pumping energy use are inversely related. This is a well-known result as systems with small pipe diameters (with low capital costs) have a higher
annual pumping energy use due to frictional losses, while large-diameter systems (with high capital costs) have a lower annual pumping energy use. Figure 4.3c also indicates that for high and low capital costs, changes in pipe diameter affect capital cost more significantly than annual pumping energy use due to upper and lower pumping energy thresholds in the Anytown layout. These upper and lower energy thresholds can be attributed to the hydraulic grade line limitation of the system, which is determined by available pressure head in the Anytown system.
Figure 4.3: Pareto-optimal fronts for a) capital cost versus EI index, b) annual pumping energy use versus EI index, and c) capital cost versus annual pumping energy use for optimization runs with and without the EI index objective.
Figure 4.3 (continued): Pareto-optimal fronts for a) capital cost versus EI index, b) annual pumping energy use versus EI index, and c) capital cost versus annual pumping energy use for optimization runs with and without the EI index objective.

The inverse relationship between capital cost and the EI index, and the linear relationship between annual pumping energy use and the EI index indicated in Figures 4.3a and b are explained further here. To detail this explanation, the environmental impacts of the two solutions labeled “Low capital cost/high energy use” and “High capital cost/low energy use” at opposite extremes of the Pareto fronts in Figures 4.3a and b were investigated. The relative contribution of lifetime pumping energy use, pipe manufacturing, and tank manufacturing and construction to the EI index for these two solutions are indicated in Figures 4.4a and b. Note that for both solutions, lifetime pumping energy use dominates the majority of environmental measure indices when compared with pipe and tank manufacturing. Further, the value of environmental measures in Table 4.1 were calculated for $1 million dollars (purchaser price) worth of production of ductile iron pipe, tank manufacturing, and electric power generation for pumping with the EIO-LCA model (Carnegie 2009) and indicated in Table 4.6. The results in this table suggest that electric power generation for pumping has significantly higher environmental measure values than pipe...
and tank manufacturing for sulfur dioxide and nitrogen oxide emissions, coal and natural gas consumption, global warming potential and air releases. Thus the inverse relationship between capital cost and the EI index, and the linear relationship between annual pumping energy use in Figures 4.3a and b are explained by: 1) the dominance of lifetime pumping energy use in the EI index, and 2) the higher environmental measure values and impacts linked to electric power generation for pumping relative to pipe and tank manufacturing. The dominance of pumping energy and its higher environmental impacts means that increasing capital cost of pipes will decrease annual pumping energy use and the EI index (inverse relationship in Figure 4.3a) and increasing annual pumping energy use will increase the EI index (linear relationship) in Figure 4.3b.
Figure 4.4: Proportional contribution of pumping energy, tank manufacturing, and pipe manufacturing to environmental measure totals for: a) “Low capital cost/high energy use” solution, and b) “High capital cost/low energy use” solution.
Table 4.6: Environmental measure values per million dollar (purchaser price) worth of production of ductile iron pipe and tank manufacturing, and electric power generation.

<table>
<thead>
<tr>
<th>Environmental measure</th>
<th>Ductile iron manufacturing</th>
<th>Tank manufacturing and construction</th>
<th>Electric power generation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sulfur dioxide (t)</td>
<td>1.20</td>
<td>1.26</td>
<td>46.90</td>
</tr>
<tr>
<td>Carbon monoxide (t)</td>
<td>7.49</td>
<td>7.08</td>
<td>6.53</td>
</tr>
<tr>
<td>Nitrogen oxides (t)</td>
<td>1.29</td>
<td>2.55</td>
<td>22.40</td>
</tr>
<tr>
<td>VOCs (t)</td>
<td>1.09</td>
<td>4.40</td>
<td>1.20</td>
</tr>
<tr>
<td>Particulate matter &lt; 10µm (t)</td>
<td>0.335</td>
<td>0.490</td>
<td>1.190</td>
</tr>
<tr>
<td>Coal (TJ)</td>
<td>1.73</td>
<td>1.61</td>
<td>84.10</td>
</tr>
<tr>
<td>Natural gas (TJ)</td>
<td>2.79</td>
<td>2.45</td>
<td>19.70</td>
</tr>
<tr>
<td>LPG, distillate, residual (TJ)</td>
<td>1.059</td>
<td>6.433</td>
<td>4.363</td>
</tr>
<tr>
<td>Jet and motor fuel (TJ)</td>
<td>1.793</td>
<td>0.749</td>
<td>0.262</td>
</tr>
<tr>
<td>Global Warming Potential (t_{CO2})</td>
<td>613</td>
<td>899</td>
<td>9530</td>
</tr>
<tr>
<td>Air releases (kg)</td>
<td>147</td>
<td>89</td>
<td>1300</td>
</tr>
<tr>
<td>Water releases (kg)</td>
<td>35.3</td>
<td>31.6</td>
<td>17.1</td>
</tr>
<tr>
<td>Land, underground releases (kg)</td>
<td>737.30</td>
<td>438.4</td>
<td>632.62</td>
</tr>
<tr>
<td>POTW, offsite transfers (kg)</td>
<td>178.9</td>
<td>123.2</td>
<td>151.5</td>
</tr>
</tbody>
</table>

The capital cost, annual pumping energy use, and environmental impact index of the “Low capital cost/high energy use” and “High capital cost/low energy use” solutions are compared in Table 4.7. The “Low capital cost/high energy use” solution has a higher annual pumping energy use (5.34 million kWh/yr) and the EI index (0.635) than the “High capital cost/low energy use” solution (3.39 million kWh/yr and the EI index of 0.474). As indicated in Figures 4.4a and b and Table 4.6, this result is owing to the dominance and higher impacts of electricity generation for pumping over pipe and tank manufacturing in the majority of environmental measures of the EI index. A comparison of category indices between the two solutions in Figure 4.5 further points to this.
Table 4.7: Capital cost, annual pumping energy use, EI index, and cost breakdown for: 1) “Low capital cost/high energy use” solution, and 2) “High capital cost/low energy use” solution (all costs in million dollars).

<table>
<thead>
<tr>
<th>Objectives</th>
<th>Low capital cost / high energy use</th>
<th>High capital cost / low energy use</th>
</tr>
</thead>
<tbody>
<tr>
<td>Capital cost</td>
<td>3.85</td>
<td>5.90</td>
</tr>
<tr>
<td>Annual pumping energy use (million kWh/yr)</td>
<td>5.34</td>
<td>3.39</td>
</tr>
<tr>
<td>EI index</td>
<td>0.635</td>
<td>0.474</td>
</tr>
<tr>
<td>New and parallel pipes</td>
<td>3.31</td>
<td>5.36</td>
</tr>
<tr>
<td>Cleaning/lining</td>
<td>0.002</td>
<td>0.002</td>
</tr>
<tr>
<td>New tank</td>
<td>0.54</td>
<td>0.54</td>
</tr>
</tbody>
</table>

1All costs are in million dollars

Figure 4.5: Category index values for “Low capital cost/high energy use” solution, and “High capital cost/low energy use” solution.

Figures 4.3a-c also feature a transition point, or gap, in the Pareto-optimal solutions. The solutions on either side of this gap feature the same tank diameter and the same cleaning and
lining costs but differ minimally in pipe expenditure. Although this change in pipe diameter is minimal, the pumping energy use of the system is affected more significantly by the change in pipe diameter and the resultant EI index is subsequently affected more significantly. At this transition point, the pumping energy use of the system (and the EI index) is highly sensitive to small changes in pipe diameter.

The impact of the EI index objective on the optimization was also investigated. Figure 4.3c compares Pareto-optimal solutions generated by minimizing capital cost, annual pumping energy use, and the EI index with those solutions where the EI index objective was excluded from the optimization. Two observations are made in Figure 4.3c: i) the solutions in the Pareto front generated with the EI index objective had a similar range of a pumping energy use values when compared with those in the Pareto front generated without the EI index objective; ii) the Pareto front generated with the EI index objective lies in a slightly higher capital cost range than the Pareto front generated without the EI index objective. These preliminary results suggest that including the EI index objective in the optimization can lead to solutions with similar pumping energy use and, in some cases, slightly higher capital cost relative to solutions generated in optimization runs that exclude the EI index objective. This is likely due to pumping energy dominance in the EI index, which tends to produce systems with higher capital costs in order to minimize pumping energy use and EI index values.

4.6.2 Sensitivity Analysis

A sensitivity analysis was performed to determine the sensitivity of Pareto solutions to demand and ‘C’ factor uncertainties. In the first part of the analysis, diurnal pattern multipliers, the MHD peaking factor, and the MDD peaking factor in the baseline scenario (described above) varied by ±10% and ±30% to model 4 realistic scenarios. Figure 4.6a shows the interplay between annual pumping energy use and capital cost for each demand scenario. The Pareto solutions in the +30% demand scenario were assigned large tank capacities, large pipe diameters, and additional cleaning and lining to meet the high demand requirements. The larger tank capacities allowed more water to be pumped to the storage tanks during low-demand periods, which increased annual pumping energy use relative to the baseline scenario. The Pareto solutions in the +10% demand scenario adjusted to demand increases by adding capacity through additional cleaning and lining relative to the baseline scenario. In addition, the results in Figure 4.6a suggest that
increasing demands by +10% and +30% increased the number of constraint violations, decreased the number of feasible solutions, and thus lowered the diversity of pumping energy use values in the solutions in these Pareto fronts relative to the baseline scenario. The results in Figure 4.6a also suggest that decreasing the water demand increased the number of feasible solutions and lowered annual pumping energy use. Specifically, the -30% water demand scenario produced more diverse solutions (i.e. various tank diameters, different combinations of pipe diameters, and variations in cleaning and lining costs) with lower annual pumping energy use, relative to the baseline scenario. The -10% water demand scenario included smaller pipe diameters than in the baseline scenario, which led to similar pumping energy use but lower capital costs when compared to the baseline.
Figure 4.6: Sensitivity of Pareto-optimal fronts: a) capital cost versus annual pumping energy use; b) annual pumping energy use versus EI index for baseline solutions and solutions with ±10% and ±30% variations in water demand.
The results in Figure 4.6b suggest that changes in demand affect the relationship between capital cost and pumping energy use and the contributions of these objectives to the EI index. The +10% and +30% demand scenarios produced solutions with a narrow range of pumping energy use and higher pumping energy use than in the baseline scenario. In these scenarios, pumping energy use dominated the numerical value of the EI index and many solutions had similar levels of pipe and tank capacity to reduce pumping energy use. Baseline solutions in Figure 4.6b showed a broad range of pumping energy use values with some solutions focused on minimizing capital costs and others focused on minimizing pumping energy use. In these baseline solutions, pumping energy use drove—but did not dominate—the numerical value of the EI index. The results in Fig. 6b suggest that decreasing demand by 10% and 30% increased the diversity of solutions and gave pipe-related environmental impacts a larger role in establishing the numerical value of the EI index, relative to the baseline scenario. For example, the -30% demand scenario produced solutions with a broad range of capital costs; some solutions focused on lowering capital costs and others on lowering annual pumping energy use. The ‘V’ shape of the Pareto front in the -30% scenario is explained by the variable contribution of environmental impacts linked to new pipes, cleaning and lining, and new tanks in the EI index. Solutions on the left-hand limb of the ‘V’-shaped front (Figure 4.6b) had high capital requirements and low pumping energy requirements, such that environmental impacts linked to new pipes, cleaning and lining, and new tanks dominated the EI index and increased its numerical value. Conversely, solutions on the right-hand limb of the ‘V’-shaped front (Figure 4.6b) had lower capital requirements and higher pumping energy requirements, such that environmental impacts linked to pumping energy use dominated the EI index and increased its numerical value. When compared to the baseline, the -10% demand scenario resulted in solutions with a lower range of pumping energy use values and capital costs resulting in a lower range of EI index values in Figure 6b for this demand scenario.

In the second part of the sensitivity analysis, pipe ‘C’ factors were varied. The Anytown problem outlined above used manufactured-specified ‘C’ factors of 140 for cement-mortar lined ductile iron pipe for the first 10-year demand period and ‘C’ factors of 130 for the second 10-year demand period. The sensitivity analysis considered a ‘C’ factor of 125, 135, and 140 for the second 10-year demand period. Higher ‘C’ factors (135 and 140) decreased capital costs and decreased annual pumping energy use while lower ‘C’ factors (125) generated similar results as the baseline scenario. Both high and low ‘C’ factor scenarios produced minimal changes in
capital costs and pumping energy and thus did not affect the relationship between the EI and pumping energy use and EI and capital cost observed in the baseline scenario.

4.7 Broad Design Implications and Future Work
The inclusion of multiple environmental measures into a single index enables decision makers to gain a broader view of the environmental impacts linked to a network solution. This is valuable as it minimizes the chance of encountering environmental problem-shifting when only 1 or 2 environmental measures are considered in the optimization. The EI index allows decision makers to “dissect” promising Pareto optimal solutions and evaluate their category indices and individual environmental measures in post-optimization analysis. This allows decision makers to consider environmental concerns alongside capital and operating cost concerns in network design. Future research will focus on evaluating the impact of category weights in the EI index, and applying the EI index to pipe material selection in more complex systems.

4.8 Summary and Conclusions
The paper presented a new approach that incorporates multiple environmental impacts into a multi-objective WDS optimization. The environmental impacts of the Anytown problem were measured with the EI index from Herstein et al. (2009). The non-dominated sorting genetic algorithm (NSGA-II) proposed by Deb et al. (2002) was used to minimize capital costs, annual pumping energy use, and the EI index in the Anytown problem. It was shown that including the EI index objective in the multi-objective optimization minimized environmental impacts resulting from system solutions while producing system designs that were similar to those obtained from optimization runs that did not consider the EI index objective. Pumping energy use was found to dominate the EI index whereby capital cost and the EI index were inversely related and annual pumping energy use and the EI index followed a near linear relationship. A sensitivity analysis suggested that the relationship between the EI index and capital cost and the EI index and energy expenditure is sensitive to uncertainties in water demand. This relationship is less sensitive to changes pipe ‘C’ factors.

4.9 References


Chapter 5

Summary and Conclusions

Municipalities are dealing with aging water distribution systems (WDS) while faced with the prospect of increasing water demands from an anticipated change in climate. In some jurisdictions, these factors are forcing water utilities to plan system expansions to deal with these stressors. The complexity of WDS expansion decisions, combined with limited infrastructure funding has encouraged researchers to develop optimization algorithms that generate expansion solutions that balance cost and performance objectives. In addition, municipalities are starting to recognize the importance of environmental impacts and the use of non-renewable energy resources when making infrastructure decisions. Therefore, there is a need for a WDS expansion optimization framework that considers system cost and performance along with environmental impacts.

This thesis has made three research contributions that begin to address the need to balance cost, performance, and environmental concerns in WDS expansion optimization. The first contribution is the development of the environmental impact (EI) index. The EI index is a comparative index that reflects the value of a number of environmental impact measures of one WDS expansion solution relative to measure values of other solutions. This allows decision makers in water utilities to compare expansion solutions on the basis of their combined impacts. In addition, the index considers broader stakeholder concerns by grouping individual environmental measures into environmental categories that can be weighted to further reflect the prioritization of specific environmental issues.

The second contribution is the combination of the EI index with the non-dominated sorting genetic algorithm-II (NSGA-II). This new multi-objective optimization approach is the first ever in the water distribution system analysis literature that incorporates multiple environmental impact concerns into the expansion optimization of water distribution networks.

The third contribution is the application of the new EI index-based multi-objective optimization approach to a realistic network. The application of the new optimization approach to the realistic
“Anytown” benchmark system has contributed to the understanding of how incorporating environmental impact concerns in WDS design and optimization influences the search process and the optimization solutions.

In Chapter 3, the EIO-LCA-based EI index was presented and the role of the index in multi-objective WDS expansion optimization was outlined. The multi-objective EI index method was applied to the design of a simple pump-pipe transmission system for which all possible expansion solutions were enumerated and compared. The results suggested that pumping cost dominated the EI index and its composite measures. Although pipe size selection did not directly influence total cost or the EI index, the indirect influence of pipe sizing on pumping energy cost and the EI index was significant.

A multi-objective WDS expansion optimization approach that minimizes the three objectives of capital cost, annual pumping energy use, and the EI index was presented in Chapter 4. This multi-objective non-dominated sorting genetic algorithm-II-based framework was applied to the “Anytown” water network expansion problem to illustrate the ability of the method to choose solutions from a large solution space that best balance the capital cost, energy use, and environmental impact objectives. The results suggested that incorporating the EI index objective into the multi-objective optimization framework minimizes the overall environmental impact of system solutions and produces system solution that are similar in capital cost and pumping energy use when compared to Pareto-optimal solutions that were generated without the EI index objective. In addition, pumping energy use dominated the EI index resulting in a nearly linear relationship between the EI index and pumping energy use and an inverse relationship between the EI index and capital cost. A sensitivity analysis showed that uncertainty in water demands can change the balance of the three objectives thereby affecting the relationship between the EI index and capital cost and the EI index and annual pumping energy use.

The consideration of multiple environmental impact measures through the use of the EI index in the multi-objective optimization approach can assist decision makers in choosing a preferred solution on the Pareto front. In post-optimization decision making, the EI index of promising solutions can be dissected into their component categories or measure values to examine specific policy issues or impacts that might be of greater interest to a particular stakeholder.
The contributions of this thesis have laid the foundation to answer additional questions surrounding the use and application of the EI index in multi-objective decision making. Neither of the case studies presented in this thesis considered unequal weighting of environmental categories in the EI index. It will be valuable to understand the sensitivity of the model to weighting coefficients assigned to category indices in order to develop guidelines for assigning values to these weights. In both case studies of this thesis, one material was chosen for all pipes prior to optimization. Future work will investigate the costs and supply-chain environmental impacts of pipe materials (e.g., high-density polyethylene, polyvinyl chloride, concrete, etc) and tank materials. Future work should also explore the role of the EI index in the post-decision making process to further take advantage of the information contained in the EI index for the purpose of choosing a single solution from the set of Pareto-optimal solutions.