DISSERTATION

OPTIMAL SENSOR PLACEMENT FOR SEWER CAPACITY RISK MANAGEMENT

Submitted by

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ABSTRACT

OPTIMAL SENSOR PLACEMENT FOR SEWER CAPACITY RISK MANAGEMENT

Complex linear assets, such as those found in transportation and utilities, are vital to economies, and in some cases, to public health. Wastewater collection systems in the United States are vital to both. Yet effective approaches to remediating failures in these systems remains an unresolved shortfall for system operators. This shortfall is evident in the estimated 850 billion gallons of untreated sewage that escapes combined sewer pipes each year (US EPA 2004a) and the estimated 40,000 sanitary sewer overflows and 400,000 backups of untreated sewage into basements (US EPA 2001). Failures in wastewater collection systems can be prevented if they can be detected in time to apply intervention strategies such as pipe maintenance, repair, or rehabilitation. This is the essence of a risk management process.

The International Council on Systems Engineering recommends that risks be prioritized as a function of severity and occurrence and that criteria be established for acceptable and unacceptable risks (INCOSE 2007). A significant impediment to applying generally accepted risk models to wastewater collection systems is the difficulty of quantifying risk likelihoods. These difficulties stem from the size and complexity of the systems, the lack of data and statistics characterizing the distribution of risk, the high cost of evaluating even a small number of components, and the lack of methods to quantify risk.

This research investigates new methods to assess risk likelihood of failure through a novel approach to placement of sensors in wastewater collection systems. The hypothesis is that iterative movement of water level sensors, directed by a specialized metaheuristic search technique, can improve the efficiency of discovering locations of unacceptable risk. An agent-based simulation is constructed to validate the performance of this technique along with testing its sensitivity to varying environments. The results demonstrated that a multi-phase search strategy, with a varying number of sensors deployed in each phase, could efficiently discover locations of unacceptable risk that could be managed via a perpetual monitoring, analysis, and remediation process. A number of promising well-defined future research opportunities also emerged from the performance of this research.

ACKNOWLEDGMENTS

This work would not have been possible without the financial support and job flexibility of my employer, ADS, LLC. I am especially indebted to Florian Pfefferle, Group President, who has been supportive of my academic pursuits even when it was a distraction to my professional life. Special thanks to Pat Stevens and Kevin Enfinger at ADS, who served as valuable sounding boards on the occasions that I got stuck.

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Words cannot express the debt I owe to my family. They allowed my academic time to invade family time very often over more than a decade. My wife, Karen, and my three children, Ben, Thomas, and Anna Katherine have been more patient than I deserved.

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OVERVIEW OF THE RESEARCH

1.1 The application

1.1.1 The nature of risk in collection system management

The overall objective of this research is to investigate improvements in risk management for linear infrastructure principally by minimizing the cost of finding the few components requiring active risk management through new methods of sensor placement. A major objective is to provide a holistic risk management framework for the prevention or mitigation of the threats posed by the loss of sewer pipe conveyance capacity, with an emphasis on preventable failures that are related to pipe blockage.

The consequences of not detecting and intervening in time to prevent wastewater collection system failures is well documented and is the subject of section 2.1. To state it succinctly, sewers literally save lives (Kesztenbaum and Rosenthal 2017). The U.S. government recognized the importance of sewer systems in the landmark Clean Water Act of 1972, setting a goal of zero water pollution discharge by 1985. This goal has not been met, with more than 50% of the river and stream miles in the United States failing to meet water pollution standards (Keiser et al. 2019).

1.1.2 The general structure of the problem

Managing the risk of failure in collection systems represents a case of a general problem structure applicable to other types of complex linear assets, such as water distribution systems, roads, railways, electrical distribution, etc. The principal challenge is to find the relatively few components, in this case pipe locations, that justify active risk management due to a risk of failure that is judged to be unacceptable. This is illustrated by the map in figure (1-1), where the gray lines indicate pipes not warranting active risk management and red lines indicate those that do.

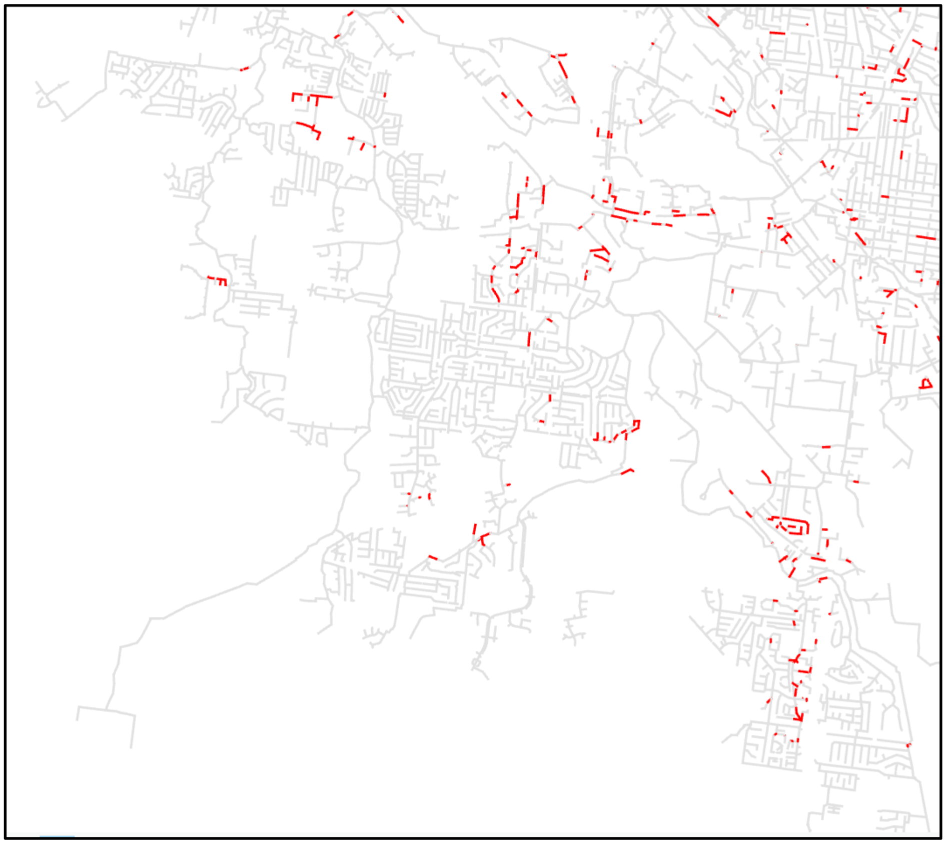


Figure 1-1: Distribution of pipe locations warranting risk management

Finding these components is a combinatorial optimization problem that is a case of the sensor placement problem. It has the following five identifying characteristics:

1.1.2.1 A combinatorial optimization objective function

The objective function corresponding to the research goal is to discover a number of locations meeting the criteria for “unacceptable risk” as efficiently as possible. The exact number of such locations is usually supplied by the stakeholders; and is driven by factors such as a capacity limit on the number of locations that can be actively managed. This objective of minimizing the cost of finding a number of locations exceeding a threshold risk may be formulated generally as shown in figure (1-2):

Variables: X_i representing all n locations in the system indexed by integer i in the range $0<i<=n$ Domains: {0,1} where $X_i = 0$ indicates the location is not actively managed and $X_i = 1$ indicates the location is actively managed Constraints: $\|\{X_i \in X \| X_i=1\}\| >= T$ where "T" is the number of locations that can be actively managed Goal: Minimize the search cost function

Figure 1-2: Objective function for minimizing the cost

This objective will be restated in terms that are specific to the wastewater collection system case presented in chapter 4 where the search cost function can be stated as a function of the unit cost and quantities of the resources deployed in the search.

1.1.2.2 It is not practical to evaluate all possible solutions

A moderate case of the wastewater collection system application would involve selecting T = 300 locations from a system of n = 11,700 candidate locations. In this case, there would be 1.953×10^{604} possible solutions. Evaluating each solution has a non-trivial cost, especially as it involves assessing risk probabilities and consequences that are not known a priori. A feature of the problem under study is that the range of available assessment technologies limits the sensing range to no more than 3-5 locations, making system-wide sensing unfeasible and limiting evaluation to only a very small fraction of possible solutions.

1.1.2.3 The solution space can be represented in a 2-dimensional Euclidean space

The candidate solutions are sets of locations that can be represented on a 2-dimensional map with locations defined by cartesian coordinates. The implication of this characteristic is that each location can be assigned to a neighborhood by a function, such as distance or nearness to a point. This property lends the problem to classes of solutions that employ neighborhood search techniques. It also lends the problem to spatial analysis, for instance cluster analysis based on distance.

1.1.2.4 The shape of the solution space is unknown

The probability of failure for candidate locations is unknown in advance of assessment. In addition, little is known about the underlying factors contributing to failure which makes prediction unreliable. This unreliability, combined with the difficulty of evaluating all solutions, favors metaheuristic search solutions. At each stage of the search only a small segment of the solution space is revealed, which will be shown to be a useful input into successive stages of a search.

1.1.2.5 The system is dynamic

Collection systems are in a constant state of change, as is the case with most complex linear assets. This contributes to the difficulty of risk management as each location can transition from fully functional, to potential failure, to functional failure over an unpredictable interval. One implication of a dynamic system is that the search for failures must be ongoing, either through perpetual search, or through a system of continuous monitoring.

1.2 Contributions to the state-of-the-art

This research study enables insights and provides methods for addressing the challenges presented by the problem.

1.2.1 A guiding risk management framework

This research produced a framework for managing risk that meets the International Council on Systems Engineering (INCOSE) recommendations for risk management. Although the application of Failure Modes and Effects Analysis (FMEA) is found in prior literature, it has not been adapted to complex linear asset failure in the manner suggested by this research. Most importantly, the problem of producing risk occurrence scores has hindered the use of FMEA. This problem was overcome in this research. Other important adaptations include the treatment of risks as either acceptable or unacceptable, in contrast to ranking based on RPN values, and a proposed rubric for risk severity scores based on satellite imagery review.

1.2.2 A strategy of iterative sensor movements

Iterative sensor movements can provide an efficient approach to assessing risk in wastewater collection systems. This research evaluated several alternative search techniques that were applied to portable continuous monitoring devices. This is a novel technique as sensors have not been utilized in this way in prior research nor practice. Traditionally, wastewater collection system sensors have been placed based on terminal nodes of drainage basins or in known “hot spots” where failures had been observed. Another approach found in potable water distribution systems is the “lift and shift” concept for leak detection, which is a sequential search technique. This was found to be an inefficient approach in this research.

1.2.3 A novel method to estimate the likelihood of failure

Another important contribution from this research is a methodology of producing risk occurrence scores based on limited continuous monitoring data. To pursue the goal of minimizing the cost of searching for risky locations, the monitoring periods in each search iteration must be small. This required new methods for estimating the likelihood of failure and translating them into risk occurrence scores on a 1-10 scale for a FMEA. This is accomplished in this research by developing a binary logistic regression model combined with a Morgan-Mercer-Flodin growth model to predict pipe failures based upon depth-duration frequencies. The depth-duration frequencies are constructed from time-series data available from level monitors.

1.2.4 Sensor movement based on a metaheuristic algorithm

This research proposes the allocation and movement of sensors within the sewage networks directed by a metaheuristic search algorithm. The category of metaheuristic search algorithms termed “trajectory methods” is found appropriate for the structure of the problem. Specifically, simulated annealing presented several attractive properties that made it the preferred base algorithm. Three adaptations of simulated annealing were analyzed in this research for determining optimal parameters and comparing head-to-head search efficiency. A sequential search and greedy algorithm were also tested for comparison. The recommended algorithm, termed “enhanced simulated annealing” (ESA) is an adaptation of base simulated annealing that takes advantage of the prior knowledge of risk consequences. ESA modifies the base simulated annealing algorithm by performing preliminary iterations using a varying number of monitors in each iteration to gain approximate knowledge of the search space. An additional research advance is the incorporation of a unique adaptative neighborhood function dependent upon the risk priorities of locations monitored in prior iterations and utilization of a neighborhood function that depends on a nearest given number of candidate locations rather than distance.

1.2.5 The development of an agent-based simulation

No models nor field techniques were found in research nor practice to test the performance of search techniques for the exploration of failure risk in complex linear assets. This research demonstrates that an agent-based simulation can model the distribution of risk across a wastewater network and simulate the movement of sensors in accordance with metaheuristic search algorithms. A considerable amount of effort of this research was expended in creating this simulation model. Various algorithms were tested in the simulated environment using Design of Experiments (DOE) methodology. Screening and optimization experiments were conducted on the various search algorithms to find the best combination of search parameters across a variety of environments, including stochastic distributions of risk across the search space. Moreover, a sensitivity analysis was conducted using the simulation with multiple parameters capable of modifying the environment.

SCOPE OF THE RESEARCH

2.1 Research context

Sewers are a necessary foundation of our modern civilization as they are a critical infrastructure component for both the human health and the water environment. This importance was highlighted by the readers of the British Medical Journal in January 2007 as over 11,000 of them chose “the sanitary revolution”, connecting people’s homes both to clean piped water and to sewers in order to dispose of their waste, as the most important medical milestone since 1840. They even thought it was more important than antibiotics, vaccination or the discovery of the structure of DNA (Ferriman 2007). For example, in October 1764, fifty percent of the deaths in London occurred among children under five years old, a situation worse than the one found in the poorest nations of our world today. Moreover, life expectancy at birth in the industrialized towns of England in 1840 was only 17 years due to the high prevalence of diseases as a result of lack of clean water and sanitation, inadequate personal hygiene, poor housing and malnutrition (Rautanen et al. 2010).

Reliable sanitation remains a challenge. In the U.S., the condition of wastewater collection systems is unacceptable and trending worse. One third of the waterways covered by the Clean Water Act fail to meet their intended usage. In the 2004 EPA Report to Congress on the Impacts and Controls of CSOs and SSOs, the agency reported that 850 billion gallons of sewage discharged to the environment from combined sewer overflows, and as much as 10 billion gallons from separate sanitary sewers (US EPA 2004b). Furthermore, as seen in figure (2-1), the same report identified that blockages were the main cause for sanitary sewer overflow (SSO) events with 48% followed by wet weather & I/I, which are forms of rain and groundwater intrusion, with 26% of the total number of SSO events (US EPA 2004b). Sanitary sewers are the focus of this research due to their high proportion of overflows caused by blockage. Blockage issues can commonly be remediated through pipe cleaning or root removal, which can be performed quickly and at relatively low cost. Combined sewer overflows caused by wet weather require more expensive and time-consuming risk interventions. Although there is very little summarized data on the number of overflows since the 2004 report, estimates show little change in the last decade.

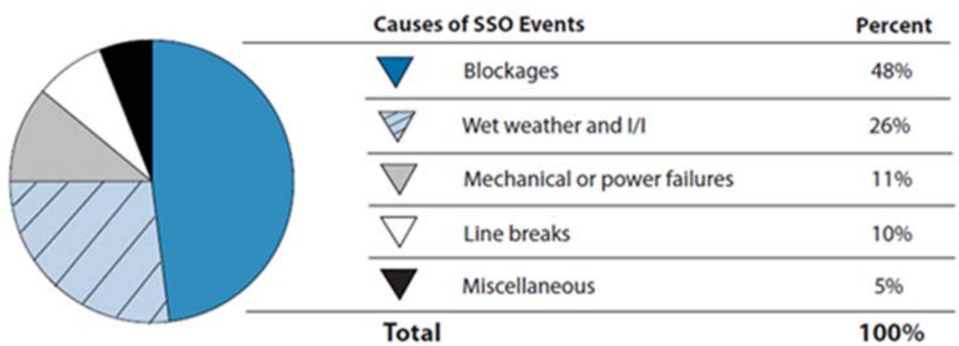


Figure 2-1: Causes of SSO events (U.S. EPA 2004)

The 2017 American Society of Civil Engineers Report Card on Infrastructure gave the country's wastewater infrastructure a grade of D+. According to that report, a total of $271 billion will be needed over the next 20 years just to maintain the existing assets (ASCE 2017b). Similarly, downstream indicators are no better. EPA's National Rivers and Streams Assessment reported that nearly half of the nation's rivers and streams are in poor condition and that the amount of stream length in good quality for macroinvertebrate condition decreased from 36.7% in 2004 to 27.8% in 2009 (U.S. EPA 2016).

In addition to the environmental and human health consequences of sewer failures, there are regulatory consequences. Reducing the unpermitted discharge of sewage is one of EPA's six national enforcement initiatives (US EPA 2019). The Clean Water Act imposes fines for up to $32,500 per day of unpermitted discharge. While this maximum fine is rarely imposed, the cost of consent decrees to avoid fines is substantial and can require decades of remediation. For example, the cost of sewer system remediation in Indianapolis, IN is $3.5 billion which is the largest civil project in the city's history (Pumphrey and Neilson 2009).

The primary dilemma faced by the wastewater systems' manager is that he or she must operate a system that complies with the EPA regulations while the system deteriorates at a rate faster than what the available funds can restore. These economic constraints motivate optimal decisions on when and where to intervene in order to preserve the capacity of the existing pipelines. As a result, there is a pressing need for new research in the area of sewage systems' decision-support tools to help local municipalities in reducing the risk of sewage systems failures while meeting their budgetary constraints. These tools should be capable of: 1) providing a framework for the perpetual management of the risk of system failure; 2) identifying where risk assessment activities should be prioritized within budget constraints; 3) providing a method for perpetual risk assessment in complex dynamic systems. Consequently, this research aims to meet these requirements for decision support.

2.2 Problem statement

To develop the above-mentioned tool, the central problem that needs to be solved by the collection systems' manager is to minimize the cost of locating and managing risks considered unacceptable. This objective is constrained by municipal budgets and often by time.

2.2.1 Definition of failure

The first step in solving this problem is to define what is the functional failure of a sewage system. According to the INCOSE Systems Engineering Handbook, failure is defined as the event when one or more parts of a system does not perform according to its specification (INCOSE 2007). In the context of sewage systems, a sewer pipe is designed to maintain free capacity to accommodate future service demands and provide a contingent capacity to convey peak volume during storm events (Washington Suburban Sanitation Commission 2017). There are other failure modes for sewers, including structural failure and odors, which are outside the scope of this research.

For the purposes of this research, a failure is defined as the condition where the water level in a pipe exceeds the pipe height. The ratio of water level to pipe height is commonly referred to as the depth-to-diameter ratio, or d/D ratio. Therefore, a failure in the sewage pipe is the condition where the d/D ratio is greater than 1 and the pipe has no free capacity for conveyance. This state is also referred to as “surcharge”, which is defined by Yen, Chie, and Nicholas as “the situation in which the sewer entrance and exit are submerged, and the pipe is flowing full and under pressure” (1980). Failures are most evident when wastewater escapes the system. One of the most obvious signs of failure is surcharge or flooding at specific manholes in the system (Thorndahl and Willems 2008). A less obvious sign of failure is the flooding of subsurface structures, such as basements, which is possible without experiencing surface flooding (Schmitt, Thomas, and Ettrich 2004).

2.2.2 Solution requirements

The central challenge with sewage system's risk management is how to select the set of locations to assess failure states. One solution to the problem of system-wide risk assessment would be to place sensors in every manhole of the sewer system so that every hydraulic anomaly (potential failure) could be detected at all times. Nonetheless, this solution is cost prohibitive given today's technology. Furthermore, this solution will also be wasteful as much of the information would be redundant. A slightly less impractical solution would be to place sensors in every manhole where a potential failure will occur in the future. Unfortunately, it is impossible to know where failures will occur in the future in the absence of monitoring, making this solution unfeasible. Another practical but imperfect solution would be to place as many sensors as can be afforded into manholes that have the highest estimated probability of failure. This would require that monitors be relocated periodically, as risk in some pipes are reduced by maintenance, repair, and replacement activities while risk in other pipes is increased by the dynamic failure mechanisms such as pipe deterioration.

Given the above challenges, a reasonable objective to solve this problem is to discover a number of locations meeting the criteria for "unacceptable risk" as efficiently as possible. The exact number of locations depends upon the capacity of available maintenance resources. The solution will be a discrete subset of sensing locations from a known set of candidate locations. This is often referred to in literature as the "sensor placement problem".

These problems lend themselves to combinatorial optimization solutions including simulated annealing, tabu search, and genetic algorithms. "These methods cannot guarantee convergence to the global optima but can uncover useful local optima after examining a tiny percentage of all possible combinations of N locations taken M at a time" (Padula and Kincaid 1999 p.3). Each of the heuristic methods has its own advantages. Hence, this research emphasizes the importance of judicious choice of design variables, optimization formulation, and solution method to fit each problem. The remainder of this section presents the considerations for choosing an appropriate method to evaluate combinatorial optimization algorithms with varying parameters.

First, the method must accommodate a wide range of sensing locations and available sensors. In the case of sewer networks, the solution space is very large. For instance, the average-size collection system contains 11,700 pipe segments which translates into approximately 11,700 manholes that could be selected as potential sensor locations. Assuming a sufficient budget for 2.5% coverage, this will lead to a need to select approximately 300 locations which equates to 1.953×10^{604} possible sets of locations of 300 monitors from among 11,700 monitor locations.

Second, the selected method must accommodate simulation across a geospatial network. Unlike some other sensor placement problems where sensors may be placed at any point in space or on a uniform grid, the problem under consideration only allows sensor placement at discrete locations as defined by the map of the sewer network.

Third, the method must accommodate varying degrees of spatial autocorrelation in risk. The probability of failure at any particular location is dependent in part upon the risk of the surrounding locations. This is intuitive given that a pipe shares physical and environmental characteristics with the other pipes around it. Evidence will be presented in this research to support this conclusion.

Fourth, the method must be able to rank the efficiency of various optimization algorithms. Since the cost of evaluating any particular solution is high, the best algorithms will converge quickly on a “good” solution. However, since the shape of the objective function is only discovered by placing sensors in a location set for a period sufficient to assess the probability of failure, the evaluation of each sensor combination is both time consuming and costly. Hence, testing alternative search strategies in pilot projects requires a great deal of time and money. A simulated environment overcomes this problem.

Finally, the adopted method must accommodate optimization algorithms that allow any shape of the objective function. The rationale is that since little is known about the underlying factors contributing to failure, the shape of the objective function of total risk in each possible set of monitored locations is unknown and almost certainly non-linear. This favors metaheuristic search techniques because they make few assumptions about the problem to be solved. The surface of the objective function will almost assuredly contain many local optima that might trap some classes of optimization algorithms, such as gradient search techniques.

More specifically the evaluation method must be able to model “trajectory methods” of optimization. This is a classification used by Baghel, Agrawal and Silakari (2012) to refer to metaheuristic search techniques that solve combinatorial optimization problems in a single solution evolution. This contrasts with population methods that deal with sets of solutions, such as genetic algorithms, ant colony optimization, and particle swarm optimization. Popular trajectory methods are simulated annealing, tabu search, variable neighborhood search, and greedy randomized adaptive search procedure

(Baghel, Agrawal, and Silakari 2012). The argument for excluding population techniques is that the expense and time required deploying monitors in sets of locations and evolving those sets is prohibitive.

2.2.3 Similar problems

There are other complex networks that must be monitored at a relatively small subset of locations. For example, monitoring water distribution systems for the presence of leaks is a closely related problem. The concept of “lift and shift” of acoustic listening devices exists in water distribution, thus incorporating metaheuristic search algorithms could be a possible improvement over the exhaustive search heuristics used in lift and shift projects. Furthermore, the problems of risk assessment in electrical grids, natural gas pipelines, computer networks, rivers and streams, and traffic networks, among others were considered as related problems.

2.3 Current practices and shortcomings

The current state-of-practice in managing sewer pipe failure risk depends mainly on reacting to failures, limited visual inspection data, scheduled preventative maintenance, and, in a few utilities, continuous monitoring data. Figure 2-2 illustrates how various sources of data serve as inputs to maintenance decisions.

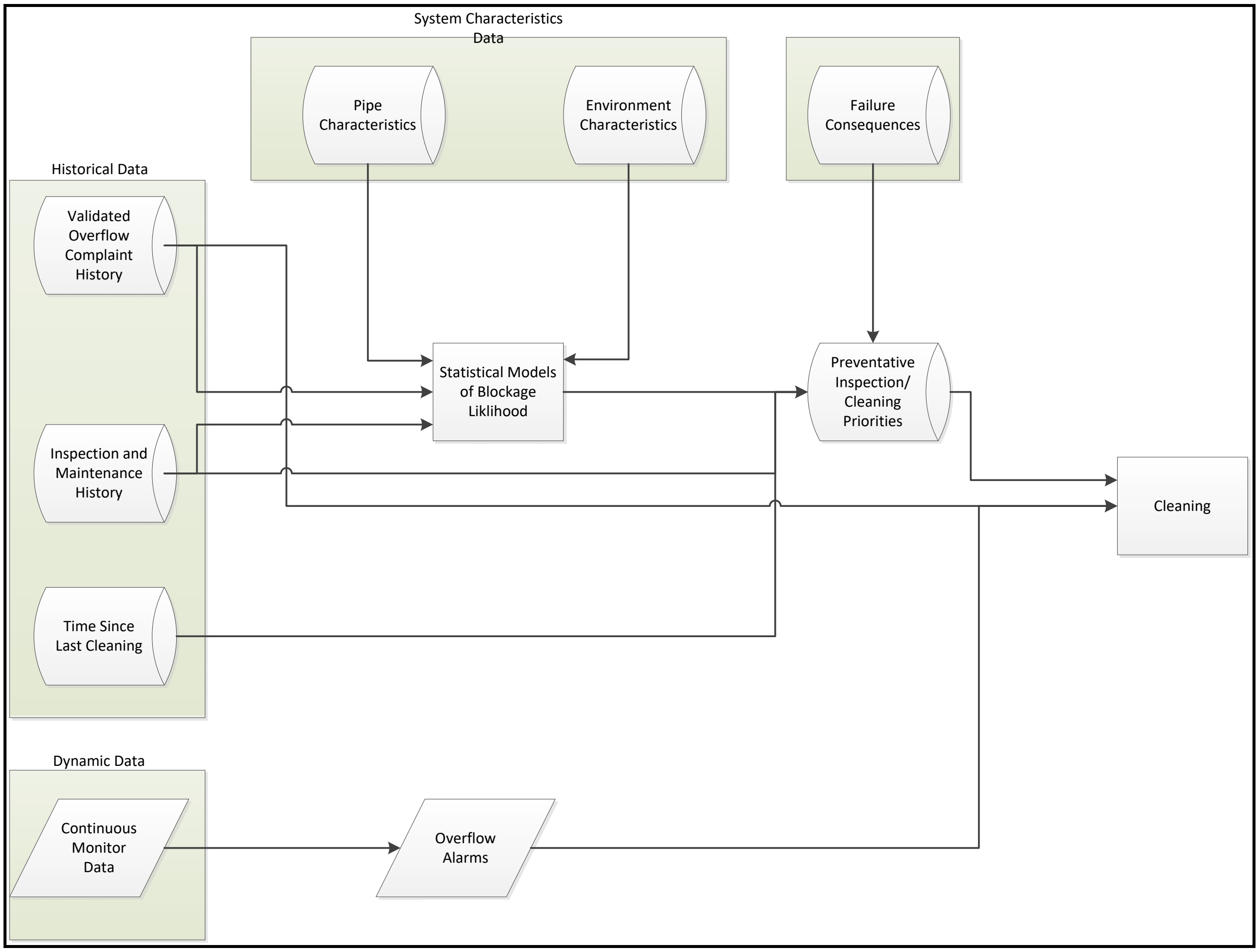


Figure 2-2: Sewage blockage management state-of-the-practice

Reactive policies are not effective. Utilities that act only after an overflow is reported are exposing themselves to legal action by their environmental regulators. Additionally, a reactive approach compromises customer satisfaction that increases the risk of bad publicity and political impairment of elected officials. Moreover, allowing overflows also imposes a financial burden as “sewage overflows already cost billions every year in cleanup, emergency repair, lost tourism revenue, lost productivity, and medical treatment.” (Dorfman, Stoner, and Merkel 2004 p.vi).

Complaint data is often unreliable. In 2007, a 7.5-million-gallon spill in the City of San Diego took 3 days to discover because the failure occurred in a pipe underneath the Buena Vista Lagoon (San Diego Coastkeeper 2016). A report commissioned by the

EPA noted that special care should be taken to inspect manholes along streams because they could overflow undetected for long periods (Nelson, Habbian, and Andrews 2000). The Environmental Integrity Project, an environmental advocacy group, charged that the City of Baltimore intentionally underreported sewage overflows by showing zero-gallon overflows in 55% of the reported incidents (Pelton et al. 2015). The EPA reported to congress in 2004 that those communities that report large numbers of SSO events are likely to be accurate because the low-volume SSO events are potentially unnoticed or unreported in other jurisdictions (US EPA 2004a).

Inspection and preventive cleaning programs are inherently limited. Among the limitations are;

1. Inspection frequency is too long to detect rapidly developing failure modes.
2. False negatives are common (Dirksen et al. 2013).
3. It is not possible to accurately monitor the hydraulic performance of pipes over time from inspection.
4. Inspections are expensive.
5. On-schedule maintenance, as opposed to on-condition maintenance, is wasteful and can shorten the useful life of pipes by subjecting them to excessive high-pressure cleaning.

Continuous monitoring offers a promising alternative. It provides hydraulic information to detect a hydraulic phenomenon, it addresses continuous pipe probabilities with a continuous assessment interval, and it is not prone to errors in human judgement. With new tools proposed in this research, it can prioritize locations based on a function of failure probability and consequences. The limitation of cost and resolution is addressed in this research with iterative sensor movements guided by metaheuristic search algorithms.

2.4 The role for systems engineering in collection system management

The application of systems engineering principles to linear infrastructure risk management can make a valuable societal contribution that is presently lacking. However, systems engineering is rarely observed in the literature and practice of sewer operations and maintenance. Applying a systems' engineering approach to sewers is one novelty of this research.

2.4.1 Sewers are complex systems

Systems engineering concerns itself with guiding the engineering of complex systems (Kossiakoff et al. 2011). The systems under consideration in this research are wastewater collection systems consisting primarily of interconnected pipes that transport water by gravity to a few collection points where the water is treated and then discharged into the environment. Figure (2-3) below illustrates the schematic of a wastewater collection system.

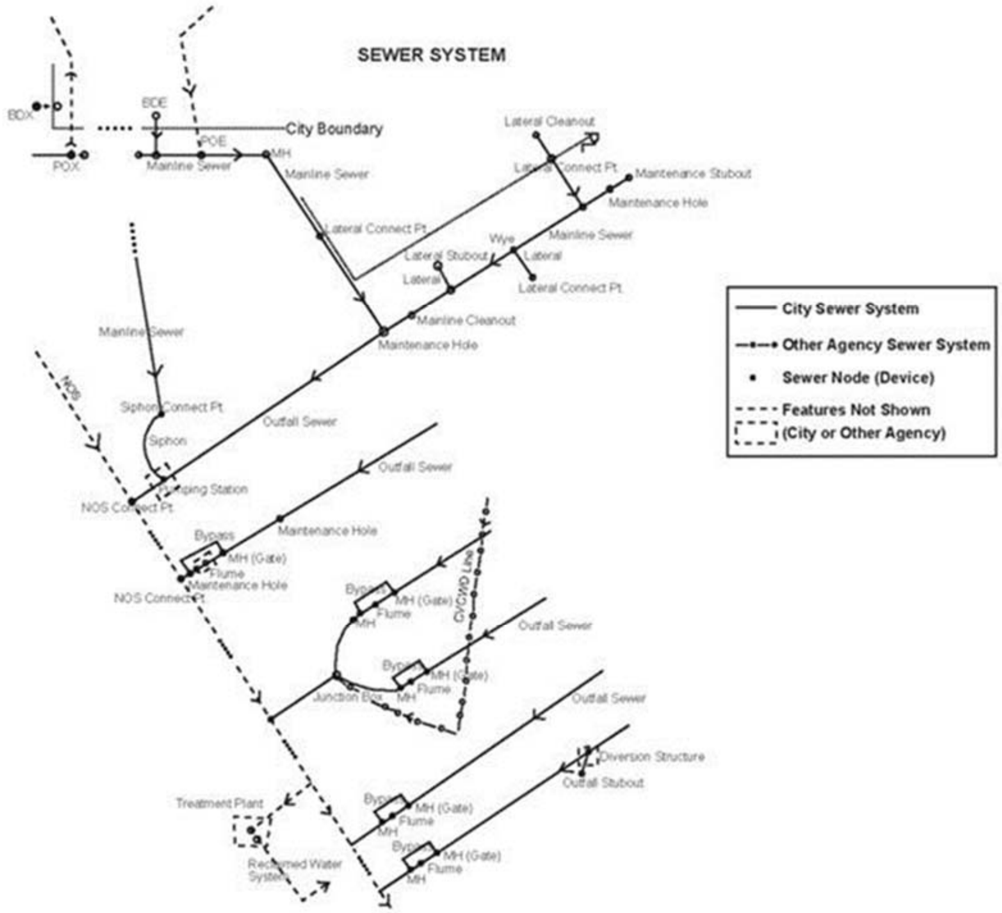


Figure 2-3: Component layout of a collection system (Hamilton Township)

What is a very simple component list becomes a complicated system in light of the environment, scale and lifespan of a wastewater collection system. Consider, for example, that the moderate-size city of Lincoln, NE, with a population of nearly 300,000, contains over 1,000 miles of sanitary sewer pipe (City of Lincoln Nebraska 2013). An estimate of the nominal length of a pipe segment is 10 feet assuming a mix of concrete and plastic pipes. This, in return, would imply 528,000 pipe connections. Each of these connections is an interface where the piping network is most vulnerable to failure. Complicating matters more is the variety of pipe ages, materials, and the surrounding environment under which this integration must succeed. In addition, these complications will increase as the user’s needs will normally change over the 50+ year useful life of the system.

2.4.2 Relevant systems engineering processes

The International Council on Systems Engineering maintains the Systems Engineering Handbook that serves as a guidance document for the profession (INCOSE 2007). Among the various processes and activities that make up the practice of systems engineering, the following are particularly relevant to the operations and maintenance of collection systems.

2.4.2.1 Maintenance process

The purpose of the maintenance process is to sustain the system through its useful life. Many collection systems have passed their design life. There is a great benefit in extending the useful life well beyond the design life due to the high cost of replacing sewer pipes. Over half of the spending in the U.S. wastewater sector goes for operations and maintenance activities (ASCE 2017a). In the maintenance process, the INCOSE Handbook recommends that problems be identified based on the feedback from ongoing monitoring of the operational environment. An output of the maintenance process is reporting of failures and recommendations for action. Also recommended is the use of historic data and performance statistics to maintain high levels of reliability and availability.

2.4.2.2 Risk and opportunity management process

Risk management is used to understand and avoid the potential cost, schedule, and performance/technical risks to a system and to take a proactive and structured approach to anticipate and manage negative outcomes. The emphasis of this research is on technical risk in terms of a collection system failing to achieve its performance requirements of transporting wastewater. This objective is a resource allocation that mitigates the most risk at the lowest cost. The INCOSE Systems Engineering Handbook prescribes the following elements of effective risk management.

1. Analysis of risk severity.
2. Analysis of risk likelihood of occurrence.
3. Quantification of risk in a methodical way. For example, Expected consequence = Probability of failure (Pf)* Consequences of failure (Cf).
4. Prioritization of risks as a function of severity and occurrence.
5. Develop criteria for acceptable and unacceptable risk.
6. Generate a plan of action for the unacceptable risks.
7. Use of measurements and statistics to help manage risks.

Nonetheless, risk management best practices have not been possible for wastewater collection systems in part because the second foundational item, the analysis of risk likelihood, has been inhibited by the lack of a method to measure risk. This obstacle is addressed by this research.

2.4.2.3 Other processes and activities

The INCOSE Systems Engineering Handbook lists other processes and activities relevant to the research, albeit to a lesser degree than maintenance and risk management. These resources include the quality process which requires measurement and systematic improvement. The continuous monitoring recommendations of this research can serve as inputs into quality management. Failures of the collection systems lead to flooding and environmental contamination that are sources of significant dissatisfaction among customers of wastewater utilities. Also, sustainment engineering helps ensure that a system continues to satisfy its objective over its intended lifetime. The consequent recommendations of this research to practitioners include ongoing assessment of performance to guide intervention in order to extend the life of the collection system. Intervention includes life extending activities such as pipe lining, pipe bursting…etc. that restore a pipe's performance to a near-new level.

In addition, system modeling is a systems engineering activity used to support decisions in the course of system operation. A model is a simpler system that approximates the behavior of the system of interest in selected areas. In this research, a novel agent-based simulation was developed to mimic the discovery of high-risk locations utilizing metaheuristic search techniques.

2.5 Research purpose and scope

The purpose of this research is to improve the selection of locations to actively manage the risk of inadequate conveyance capacity. The selection of locations decision is a sensor placement problem that is limited by the current state-of-the-art in assessing risk occurrence and by the lack of simulated environments to test sensor placement strategies. Managing risk is constrained by those same limitations.

This research is focused on the capacity issues arising from ineffective maintenance of sewage systems. Nearly half of all overflow events are due to blockage (US EPA 2004a), which can be easily prevented by timely maintenance. Other causes of overflow events, such as infiltration and inflow (I/I), are responsible for fewer overflows and typically require rehabilitation actions that are more expensive and time consuming.

It should be noted that the methods proposed in this research for risk management apply equally well to all failure modes since the decision to actively manage failing locations is based on the consequences and probabilities of inadequate capacity. Infiltration and Inflow (I/I) due to rain entering a sewer pipe, either through groundwater infiltration or surface inflow, is a prevalent failure mode that goes beyond maintenance interventions to solve. The decision to prioritize maintenance failures is simply the potential to rapidly influence risk occurrence through maintenance since I/I reduction programs can take years to plan, fund, and execute. Moreover, success in I/I reduction programs have been difficult to substantiate (Staufer, Scheidegger, and Rieckermann 2012). Therefore, all other factors held constant, an active maintenance program provides the best return on investment of the utilities O&M and capital budget.

The data collected for this research was from sanitary sewers located in the United States. However, there is no reason that the framework for risk management proposed in this research would not apply to other types of sewers in other locations. Specific parameters, such as the formula for risk occurrence estimates and the parameters for the metaheuristic search algorithm, might change for different types of collection systems in different locations.

2.6 Research goals and objectives

The research objective is to investigate improvements in risk management for linear infrastructure principally by minimizing the cost of finding the few components requiring active risk management through new methods of sensor placement. The main goal of this research is to investigate a framework for managing the risk of sewer failure due to maintenance issues. It is observed that, in practice, wastewater utilities have not adopted two of the major concepts of systems engineering in their maintenance programs that led to inefficient maintenance programs; 1) the use of continuous monitoring for maintenance planning, and; 2) the application of a risk model to actively manage the greatest threats of pipes failure. There exists a limited body of prior research along these topics however, the fundamental obstacles of quantifying risk probabilities prevent the application of these important concepts.

Regarding the first research objective, risk prioritization based upon failure consequences and failure probabilities is not a new concept and has been proposed for risk management of sewer failures (Arthur, Crow, and Pedezert 2008). However, prior research has focused exclusively on the use of historical failures to predict future failures using mathematical models rather than identifying problems based on “ongoing monitoring of the operational environment” as recommended in the INCOSE handbook (INCOSE 2007). Furthermore, while there has been considerable research into sensor placement for structural health monitoring of certain classes of systems, there is no prior research addressing the question of where to place sensors in a sewer network for maintenance management. Consequently, an objective of this research is to base maintenance decisions on monitor data while, at the same time, recognizing that it is not feasible to monitor an entire sewer system due to cost constraints. Therefore, a goal of this research is to propose an algorithm or heuristic that could guide operators to locate sensors in areas that would yield the highest value information to minimize risk of pipe failure.

The apparent absence of a method to assess risk occurrence probabilities severely limits the application of risk management models. Without a strategy of locating and moving sensors, necessary data cannot be collected upon which assessments of risk occurrence probabilities are made. Therefore, another objective of this research is to develop and apply a risk model to actively manage the greatest threats of pipes failure, guided by data.

In order to achieve these research objectives, several research questions need to be answered throughout this study. These questions are:

1. What is the appropriate risk model that reflects the nature of sewer failures and can aid in managing these failures?
2. How should differing consequences of failure be considered? For example, is actively managinging unpermitted discharges that have the highest human impact (e.g. beach closures, downtown flooding, road collapse) a higher priority than managing large pipes, such as the trunk lines of a network, that could potentially spill larger volumes if they fail?
3. How should the probability and location of occurrence of failure be assessed and what is the most easily achievable methods to detect the occurrence of failure in advance?
4. How should the sensor placement decision be made, both initially and over time?
5. How should the various sensor placement algorithms be simulated to assess their effectiveness in addressing the sewer failure problem?

6. Is there a need to develop new algorithms or can the existing placement algorithms be enhanced for this problem?

Through answering these questions, this research will be able to contribute new methods to help solve the sewer failure problem.

2.7 Research methodology

In order to achieve the above-mentioned research objectives, the research methodology is divided into five main research tasks as follows and illustrated in figure (2-4): 1) Conduct a comprehensive literature review of the latest research studies in the fields of sewer systems maintenance and optimization modeling; 2) Select an appropriate risk model for the sewage systems failure problem; 3) Develop a realistic simulation to test location selection techniques; 4) Develop an algorithm to select a search technique and determine the optimum placement of sensors; and 5) Design experiments to implement and validate the developed tool.

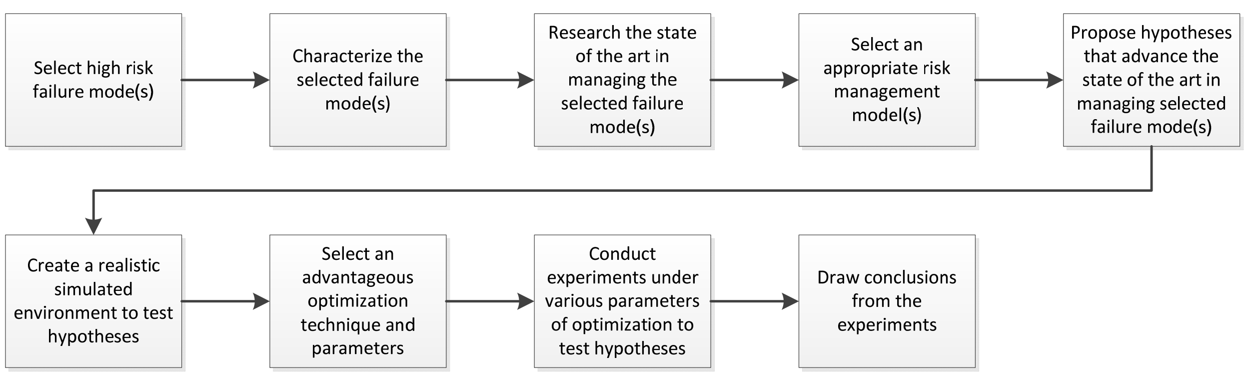


Figure 2-4: Research methodology

Each of the above five tasks will serve its role in achieving the research objectives as follows.

Task 1 (Literature Review): The goals of the literature review task are to: 1) explore the state-of-the-art for managing the specific risks of sewer systems failure due to maintenance; 2) research the state-of-the-art for sensor placement in problems with a similar structure; 3) understand of the state-of-the-art for created simulated environments for problems with a similar structure.

Task 2 (Risk Model Selection): The basic problem examined in this research can be considered an application of risk management. The best practices for risk management in systems engineering employ risk models (Haimes 2015). Of the various risk models to choose from, none is perfect but to cite the well-known quote from mathematician George Box, "essentially, all models are wrong, but some are useful" (Box and Draper 1987). Model selection itself can be a complex decision made more difficult by poor information and competing objectives (Karimiazari et al. 2011).

Task 3 (Simulation): Since field testing of various sensor placement algorithms over a sufficient variety of environments, and in a research project timeframe, is not practical in terms of both time and cost, a realistic simulation will be used as a key enabling technology of this research. In this research, three major categories of simulation were considered - discrete event, systems dynamics, and agent-based.

Task 4 (Optimization): Another enabling body of knowledge leading to efficient methods of locating sensors in order to best manage the risk of sewer failure is the field of optimization. By recognizing the problem as a combinatorial optimization problem, initial boundaries were placed on the choice of optimization techniques. Consequently, among the optimization techniques under consideration in this research were gradient methods, evolution algorithms, and heuristic search algorithms.

Task 5 (Experimentation): The implementation of search algorithms in a simulated environment allowed experiments to be conducted. The purpose of experimentation was not only to select a useful optimization technique for risk management, but also to learn how various parameters within the selected optimization algorithm affect the search efficiency.

2.8 Research significance

This research study proposes an algorithm or heuristic that will guide wastewater collection systems operators to locate sensors in areas that would yield the highest value information to minimize the risk of pipe failure. Through this research, wastewater utility operators will have access to a complete risk management framework that will improve the prevention and mitigation practices of environmental contamination due to sewer failures. The research conducted in this study is expected to provide benefits to the different stakeholders associated with waste water management. These stakeholders involve:

The public. The results of this study will both improve the public's health and economic benefits. Regarding the former, public health will be improved through reducing the frequency and severity of contamination incidents resulting from sewer failures. The public will reap economic benefits from avoiding the regulatory and cleanup costs associated with sewer spills, and from the better allocation of the existing budgets which will reduce the pressure to increase the utility's rates.

Wastewater utilities and local governments. These stakeholders will benefit from fewer and less severe sewer failures, prevention of highly publicized environmental contamination events, and elimination of the negative political and economic impacts associated with the regulatory enforcement actions.

Researchers in the field of risk management for complex systems. This research is expected to enrich the current literature on the application of well-established risk models as no prior research has either considered the use of monitoring data to assess risk occurrence probabilities or recognized an objective function based upon the efficient discovery of a minimum number of unacceptable risks. This research will also benefit researchers involved in exploring sensor placement problems with the particular defining characteristics of this research, namely:

1. The cost of evaluating each sensor combination is high.
2. The spatial resolution of each sensor combination is poor.
3. The search space is a geospatial network.
4. The shape of the objective function is unknown.

2.9 Research assumptions and limitations

In consideration of the foregoing rationale, several choices were made to potentially better meet the goals and objectives of this research. These choices are:

1. A global search algorithm will produce better sensor placement sets than informed intuition.
2. This approach is better than reactive high-frequency cleaning, i.e. waiting for someone to report an overflow and cleaning the “hot spots” more frequently.
3. The number of overflow events prevented will provide a sufficient ROI for utilities to continue to invest in this monitoring strategy.

There are several aspects of the sewage systems maintenance that were not considered in this study and were identified as opportunities for enhancing future research on these types of problems. First, the research exploits failures that are spatially autocorrelated due to underlying causes related to the local environment of the pipe or due to characteristics shared by neighboring pipes. Isolated failures, which may pose unacceptable risks, need further exploration for risk assessment. An example of this is pump station failures. Second, validation of this methodology was only possible in a simulated environment with static conditions. The methodology may require adaptations for long time periods in sewer systems to account for phenomenon such as the emergence of new clusters of failing pipes. Finally, this research is only aimed at detecting the surcharge type of failure in sewer pipes. Other types of failures may not be detected and maintained using the developed tool. For example, odors and structural failure.

2.10 Dissertation organization

This research is organized into six main chapters each contributing to the overall goals.

Chapter 1: Introduction to the general structure of the problem under study and a brief overview of the contributions made to the state-of-the-art in addressing the general problem.

Chapter 2: Context of the research topic, including the gap in the knowledge and the need for this research. In addition, the problem statement, the research goals and objectives, together with their respective research questions, are outlined. This chapter also provides a brief overview of the research methodology to be adopted in this research.

Chapter 3: This chapter is devoted to providing a comprehensive review of the existing literature concerned with the scope of this research. The chapter will examine the literature concerned with previous studies aimed at solving the sewer failure problem, pinpoint their strengths and weaknesses, and highlight the advancement in the risk management state-of-the-art that will be achieved through this research study.

Chapter 4: This chapter will elaborate on the adopted research methodology that is most suitable for conducting the primary analysis. This chapter will be dedicated to the different tasks of the adopted methodology which are: establishing a risk management framework, adaptations of FMEA, developing the search techniques, determining the appropriate methods for designing and calibrating the simulations, and design the experiments that will be used to validate this research.

Chapter 5: This chapter will present the results obtained from this research study and highlight significant conclusions. This will be followed by a discussion of these conclusions and how they enhanced the solution for the sewer failure problem.

Chapter 6: This chapter will summarize the conducted research and presents its conclusions and recommendations. The chapter outlines the various contributions of the conducted research to the body of knowledge, including recommendations for future research.

LITERATURE REVIEW

3.1. The use of statistical modeling with historical data

Several researchers have sought to construct predictive statistical models of where blockages are likely to form using the pipe and/or environmental characteristics, such as surface loads and soil types. The notion of combining available historical data with system characteristics data is very appealing because it is a preventative approach that could avoid the high cost of continuous monitoring. For this reason, the following section will provide a thorough discussion of predictive modeling and its techniques.

3.1.1 Research on blockage prediction modeling

There are several research studies that aimed at developing prediction models for sewage, or pipe, blockage in general. Fenner and Sweeting (1999) made one of the earliest investigations into classifying squares within a grid of a sewer network ranked by the need for intervention. They utilized a Bayesian technique that calculated which grid squares were at most risk from sewer failure based upon records of past failures. More importantly, they also attempted to incorporate the consequences of failure in their final rankings and concluded that the total number of past failures was the best predictor of future failures. The rationale behind this conclusion was that the physical characteristics that caused the blockage to form were not remediated by reactive maintenance, typically a simple cleaning. The researchers also recommended that geographic areas with high incidents of blockage reported should be inspected. When blockages are discovered, they recommended acting to remove the cause of the blockage, not just the symptom, so that blockages would not reoccur (Fenner and Sweeting 1999).

Baur and Herz (2002) constructed a model to predict physical deterioration of pipes for the purpose of prioritizing inspections. The authors analyzed data from the city of Dresden, concluding that sewer inspection dates, prioritized by critical condition, could be forecasted as a function of the pipe's material, period of construction, location, type of wastewater conveyed, profile, diameter, and gradient (Baur and Herz 2002). Although not directly applied to blockage, this technique of scheduling inspections based on predictor variables could be extended to blockage failure modes. Moreover, it established a relationship between pipe deterioration and blockage as pipe defects reinforce the formation of blockages.

Another study that attempted to design prediction models for blockage is the one conducted by Savic et al. (2006). In this study, the researchers considered the failure modes of collapse and blockages in a study of historical records for a large sewerage system in the United Kingdom. The objective was to prioritize inspections using the technique of evolutionary polynomial regression. They were able to produce a model identifying the most important variables and a classification scheme. However, in their conclusions, the researchers highlighted that continuous monitoring is required in order to make the appropriate intervention decisions at the optimal time. The authors also concluded that the service life of sewers could not be forecasted without reliable pipe condition information. It is also important to note that the researchers found that blockages depend on both the structural conditions and the hydraulic behavior of the fluid, which implies that structural conditions data alone would be incomplete (Savić et al. 2006).

Rodriguez et al. (2012) studied data centered approaches to prevent blockages due to sediment accumulation in Bogota, Columbia. Citing the evolutionary polynomial regression (EPR) method applied by Savic et al. (2006), Rodriguez et al. arrived to a similar conclusion as other researchers that the explanatory variables for blockage varied between sewer systems. One solution for this problem was to average EPR-based models over numerous systems (Savic, Giustolisi, and Laucelli 2009). Lastly, Ugarelli et al. (2009) developed an EPR model that predicted pipe blockages in Oslo using pipe age, diameter, slope, and total length as explanatory variables.

3.1.2 Limitations to statistical models of blockage

Despite the successes documented in past research studies, there are some limitations of failure modeling approaches based on historical data that make them unsuitable for practical use. These were highlighted through the numerous in-person interviews that were conducted with collection system operators in the United States and led to the observation that there were no cases found where predictive statistical models were in use for any purpose in managing blockage.

One of these limitations is that the consequences and likelihood of failure are rarely considered together through this type of modeling which are of a great importance to collection system operators (Arthur et al. 2009). For example, in the United Kingdom, potential overflow locations are classified as either “critical” or “non-critical” based on the economic consequences of failure (Fenner and Sweeting 1999). The State of California recognizes three categories of sewer overflows based on volume and whether or not the overflow reaches a surface water body, with greater investigation burden given to the highest volume overflows (State of California Water Resources Control Board 2013). In addition, another challenge to modeling the future blockage based on historical data is the poor quality of customer complaint and maintenance intervention data (Arthur et al. 2009).

A second limitation of this modeling technique is the time and human resources required to transform the raw data into a useful predictive model. In a study of complaint data in Edinburgh, Scotland, the researchers ran into numerous roadblocks in developing a predictive model. One significant roadblock was the manual effort required to collect and analyze the data which limited the application of their method to small catchments only (Arthur et al. 2009). Baily et al. (2015) investigated the use of decisions trees to predict blockages in Dŵr Cymru Welsh Water. The research required an elaborate set of data conditioning activities including removing duplicate records in historical data, removing or estimating values for data that appeared suspicious, development of a consistent spatial reference for linking historical data to the sewer network, interpolation of missing sewer gradient data, derivation of property density, and derivation of the concentration of food producers. In the absence of hydraulic information, the researchers estimated flow velocity using the Manning formula while assuming normal depth to estimate the sediment’s buildup risk. This elaborate combination of data cleansing and estimation is not only time consuming, but also results in a model that is dependent upon assumptions that are known to be violated in the dynamic environment of sewer networks. Fontecha et al. (2016) discovered that nearly 45% of sediment related complaints were ineffective, repeated, or wrongly classified. Fenner and Sweeting (1999) recognized these issues and concluded that in order for sewer failure to be correctly attributed to a specific pipe length, the lack of connectivity between the asset and event databases need to be overcome first, and second, the analysis must be able to handle missing data and information without recourse in order to substitute extensive quantities of default values which would distort the results and mislead their subsequent interpretation.

A third limitation of the statistical modeling technique is that the predictor variables for blockage likelihood are complex and vary between collection systems (Fenner and Sweeting 1999). This reality means that models must be constructed uniquely for every system and that the predictive power may also vary between systems. Marlow et al. (2011) conducted a survey of collection systems experts in Australia to gather their opinion on the causes of sewer blockages. The purpose of this study was to assess whether it was fair to judge water companies' performances based on blockage rates and it was concluded that it was not fair because of the city-unique circumstances leading to blockages, some of which are outside of management's control. Rodriguez et al. (2012) best summarized the prior research on predicting blockages by noting that there were various, and sometimes contradictory, explanatory variables for blockage in prior research, and that there was no consensus on the physical properties of pipes to explain blockage. After reviewing these models, the conclusion is that "…blockages often appear random with differences in blockage rates between catchments often inexplicable" (Rodríguez et al. 2012 p.4375).

Some investigators have concluded that there are inherent limitations in attempting to apply static models to the dynamic environment of sewers. For instance, Fenner and Sweeting (1999) reasoned that deterministic models for predicting sediment accumulation were questionable and likely to produce misleading results. Moreover, Rodriguez et al. (2012) concluded that sufficient data was not available and that all previous research highlights the complexity and randomness in sewer blockages. Hence to be able to accurately model the observed blockage rate, more explanatory variables should be taken into consideration. These variables include structural conditions, high resolution spatially distributed rainfall data, and water consumption rates, which are not presently available.

3.2 State of the art in sensor placement

Continuous monitoring would be ideal if 100% of the sewer system could be monitored with sufficient warning to react economically. However, cost constraints limit the number of sensors that can be deployed to only a fraction of the potential monitoring locations. The next best approach is to employ a method for prioritizing the placement of monitors amongst all potential monitoring locations. Nevertheless, there are no published research that addresses the question of where to place sensors within a collection system in order to best minimize the effects of sewer overflows due to blockage. The few utilities with documented programs of blockage monitoring have developed heuristics based on historical failures and/or areas of highest consequences should an overflow occur, for example the City of San Antonio, TX (Haby et al. 2015). Therefore, in order to examine the state-of-the-art in sensor placement, research that used sensor placement for fault detection in other applications, such as leaks in drinking water distribution systems, provides helpful analogies in advancing this area in sewage systems. See section 3.2.2, for example.

3.2.1 Sensor placement based on historical failures

The City of Atlanta, Georgia has reported success in utilizing continuous monitoring to prevent overflows. Operators place monitors in locations that have a high-priority of being a repeat spill areas (Macrina and Woodall 2016). Furthermore, the City of San Antonio, Texas has been successful in deploying level monitors as a result of root cause analysis of historical overflows (Haby 2013). This approach is consistent with the research by Fenner and Sweeting (1999) that demonstrated that the past events in a geographic grid are the best predictors of future failures. There are two main shortcomings to this approach, which are: 1) it ignores locations with unreported overflows, and 2) a significant proportion of overflows appear randomly. Nonetheless, these shortcomings do not invalidate the importance of considering historical failures when choosing sensor locations as the successes in the cities of Atlanta, San Antonio, Murfreesboro, and elsewhere are solid evidences that many blockages will reoccur in the same locations, particularly if the underlying mechanisms that cause the blockage are not addressed.

3.2.2 Sensor placement research in related applications

Sensor placement has received attention recently within the topics of structural health monitoring and fault detection and isolation. While none of the approaches has been studied to detect failures in collection systems, the methods employed were examined for their potential applicability to the blockage problem. The structure of the problem of sensor placement for blockage detection provides boundaries for suitable algorithms. Lynch (2007) used the sensor monitoring technique to detect structural damage to bridges resulting from excess loads. In this study, a first generation of structural monitoring systems was composed of sensors installed within structures that communicated raw data by wire to repositories where they were stored and post-processed to understand the vibrational characteristics, validate models, and understand nonlinear responses to loads. In addition, a case study was presented from the Alamosa Canyon Bridge in New Mexico where the wireless sensors accurately recorded vibrations induced by hammering on the bridge. Nevertheless, wireless systems have a disadvantage in that they are battery powered and the communications modules consume most of its power. Also, the computational efficiency of algorithms, such as FFT, affect battery life. Tradeoffs may be necessary in precision and temporal scale in order to achieve longer battery life. Another disadvantage of wireless systems is the lack of a common clock. The clocks on the numerous local systems will tend to drift, therefore a method is needed to synchronize the data in time (Lynch 2007). Finally, the author concludes that wireless structural health monitoring is still in its infancy and there is more research needed.

Perhaps the most related application to sewage networks is sensor placement in water distribution systems. The focus of research in water distribution has been to detect either contamination of the water supply or leakage. Like collection systems, water distribution networks are large-scale linear assets with discrete monitoring locations which lends itself to combinatorial optimization techniques. Moreover, the underlying mechanisms of failure are usually not well understood nor is the shape of the objective function.

The state-of-the-art in research of the placement of sensors in water distribution systems involves the use of various optimization algorithms to detect simulated failures in models of the actual system. Krause et al. (2008), utilized an EPANET model and compared various optimization techniques including simulated annealing. Yassine et al. (2008) approached the general problem of sensor placement for fault detection utilizing a structural model of a physical system. In addition, Aral et al. (2009) proposed a progressive genetic algorithm to locate sensors in an EPANET model that detected contamination. Finally, Casillas et al. (2013) employed a genetic algorithm to place sensors in locations that best measured the difference between water pressure in no-leak scenarios versus multiple leak scenarios.

Common to the research of sensor placement in water distribution systems is a hydraulic model of the system that can simulate various failure scenarios. Sufficiently precise and system-wide models may not be available for many wastewater utilities. Even if models are available, the techniques applied to water distribution networks do not take into account the spatial auto-correlation of failures and thus overlook an important attribute for finding clusters of defects. This is less important in the case of pressurized distribution systems where pressure sensing has a much greater range and a full system sensing is practical. However, in the researcher’s practical experience of 25 years in the wastewater monitoring industry, in the case of open channel level meters, the sensing range is very short making their optimal placement highly sensitive to the actual spatial distribution of failures. Model-based sensor placement techniques are not suitable in the case of wastewater collection systems both due to the inconsistent availability and quality of hydraulic models in wastewater utilities, and the necessity of developing an understanding of the probable failure scenarios through iterative field measurements.

3.2.3 The use of metaheuristics in sensor placement

Based on the structure of the problem investigated in this research study, the class of algorithms that fits the structure of the problem under investigation are metaheuristic search techniques that solve combinatorial optimization problems in a single solution evolution. These are classified as “trajectory methods” (Baghel et al. 2012) in which the authors identify five algorithms - Simulated Annealing, Tabu Search, Greedy Randomized Adaptive Search Procedure (GRASP), Variable Neighborhood Search, and Local Search – Basic, Iterated, and Guided.

Although there is prior research on the use of trajectory methods to solve the sensor placement problem, the applications in literature are not suited for sensors placed in linear assets like a wastewater collection system without important adaptations. Lin et al. (2005) studied the application of simulated annealing to sensor placement. They studied the class of problems where grid-based placement is suitable, such as in discriminating targets for aircraft. The simulating annealing algorithm was successful in efficient identification of a near-optimal sensor placement; however, the problem is not adaptable to collection systems. Representing a collection system as a grid ignores the important spatial autocorrelation in pipe failures, as well as, the constraint that sensors may only be placed in very defined spaces in the network (e.g. a manhole). Second, the work by Lin et al. (2005) did not have a high cost of assessing candidate solutions since it was done by computer simulation without regard to the time and expense of sensor movement iterations in practice.

3.3 Research on risk management models

Another important question to be answered in this research is what is the appropriate risk model that reflects the nature of sewer failures and offers a framework for managing failures towards some objectives. To answer this question, the different risk models need to be explored. Smith and Merritt (2002) proposes two objectives of a model of risk. The first objective is to provide a means of comparison between risks in order to select those to manage. The second is to point towards the root causes for resolving risks. Additional benefits of a risk model include communicating the nature of risk and understanding the chain of events that lead to an impact of a risk event (Smith and Merritt 2002).

3.3.1 Risk model alternatives

It is common among the literature on risk management to acknowledge that a certain degree of expert judgement is involved in assessing risks (Project Management Institute 2013). It is also recognized that the best practice includes quantitative assessment of risk in a structured way which is particularly true for the field of systems engineering (INCOSE 2007). To quantify risk accurately, different risk models combine the risk's probability and its impact which is the methodology recognized by the 2009 International Standard on Risk Management, ISO 31000:2009. The standard calls for consequences and likelihood of risk to be combined and expressed in a way tailored for the purpose of the risk management process (Purdy 2010).

Smith and Merritt (2002) proposed four alternatives for risk models - the Standard Model, Simple Model, Cascade Model, and Ishikawa Model. All these models share the elements of the probability of the risk event, the impact of risk event, and the drivers of each. The models are general purpose and do not address specifics such as the units-of-measure for quantifying a risk's impact. In the following sub-sections, a brief description about each of these models will be provided. In addition, other risk identification and quantification models include the Analytical Hierarchy Process, Fault Tree Analysis, and Failure Modes and Effects Analysis.

3.3.1.1 Standard risk model

The Standard Risk Model combines the elements of the probability of risk events, probability of the impact of the risk, and estimated total loss as numeric inputs to risk events and their impacts. The events and their impacts each can have multiple drivers that help explain their causes. This process produces an "expected loss", which is the product of elements (Pe * Pi *Li), as shown in figure (3-1). This parameter becomes the quantity to rank the risk (Smith and Merritt 2002).

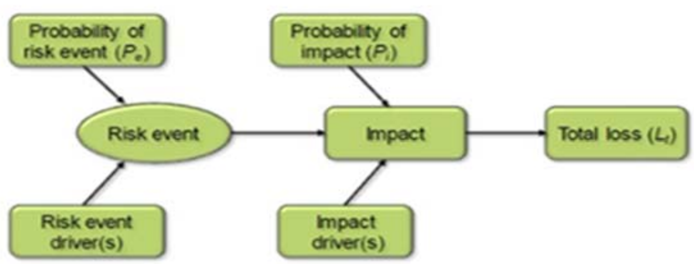


Figure 3-1: Standard risk model (Smith and Merritt 2002)

The Standard Risk Model is adaptable to a wide range of problems across industries, regardless of the size or nature of the industry (Leitch 2010). Relevant to the topic under study, Rihar (2018) successfully applied the Standard Risk model to large infrastructure construction projects. Another advantageous feature of the Standard Risk Model is a "risk map" that separates the risks that are considered critical from those considered to be non-critical. The goal of the process is to apply management actions to all critical risks until they are classified below the “threshold line” which connects points of equal expected loss. An example of a risk map is shown in figure (3-2) (Rihar et al. 2018). Other advantages of the Standard Risk Model include the identification of drivers for both events and impacts, which helps in prioritizing management actions to those causes that contribute most to the expected loss (Sturdivant 2017). Another advantage is that separating events from impacts develops a valuable understanding of cause and effect relationships (Smith and Merritt 2002). On the other hand, a drawback of the Standard Risk Model is that it does not support the selection of risk strategies (Gericke, Klimentew, and Blessing 2009). Based on the researcher’s experience with the Standard Risk Model, it would not be practical for this study due to the large number of risk events, over 14,000, that would require evaluation.

Figure 3-2: Risk map example (Rihar et al. 2018)

3.3.1.2 Simple risk model

The Simple Risk Model is a simplification of the Standard Risk Model in which the probability and drivers of the risk events and impacts are combined as illustrated in figure (3-3) (Smith and Merritt 2002). The main advantage to this model is its simplicity, as well as, the benefits of calculating an expected loss for purposes of risk ranking and an understanding of risk drivers. A criticism of the model is that it sacrifices flexibility for simplicity as separating probabilities of events and their impact can be critically insightful, particularly in the case of low probabilities and catastrophic impacts (Sturdivant 2017).

Figure 3-3: Simple risk model (Smith and Merritt 2002)

3.3.1.3 Cascade risk model

The Cascade Risk Model is similar to the Standard Risk Model with the addition of intermediate consequences associated with a probability of consequence and a set of drivers for each. This model is appropriate when failures occur in a sequence i.e. chain reaction, that culminates in a loss as illustrated in figure (3-4) (Smith and Merritt 2002). The Cascade model was applied in various fields. For instance, Zhai et al. (2017) applied the Cascade Model to power systems failures. Korkali et al. (2017) used the model to show the effects of the loss of the power grid on other critical infrastructure, like communication networks. Daqing et al. (2015) generalized the applications to all types of networks (Daqing et al. 2015). However, Smith and Merritt (2002) identify the difficulty of calculating probabilities as a drawback to the Cascade Model because risks may become so specific that they become improbable. They recommended the use of this model only to deconstruct complex risks.

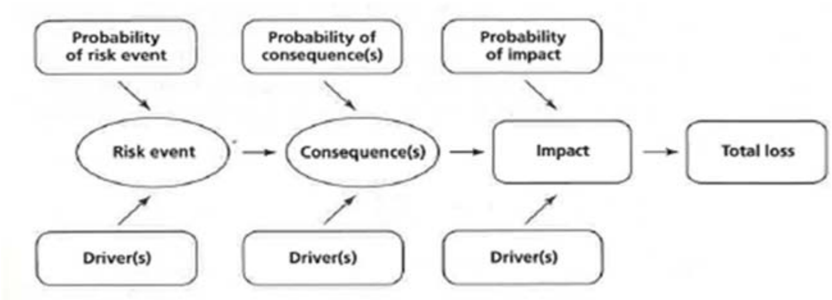


Figure 3-4: Cascade risk model (Smith and Merritt 2002)

3.3.1.4 Ishikawa risk model

Kaoru Ishikawa popularized cause-and-effect diagrams in the 1960's following the concept of Five Whys. This tool is a graphical illustration between an outcome and all of the factors that cause it, with the ultimate goal of identifying the root causes (Suárez-Barraza and Rodríguez-González 2018) as shown in figure (3-5). The Ishikawa Risk Model is appropriate when it is important to understand why a risk occurred (Smith and Merritt 2002). Jen (2010) proposed using this model to visualize risk in a technique called "Visual Ishikawa Risk Technique (VIRT)" by utilizing the Risk Breakdown Structure as a basis for events and drivers. Ilie and Ciocoiu (2010) recommend the Cascade model for events with multiple causes, arguing that an advantage is to focus the treatment on the most impactful causes. Nonetheless, many people find the Ishikawa technique overly complicated and it is recommended to use it to understand why risks occur but not for managing them (Smith and Merritt 2002). Thus, it was judged to be inappropriate for this research due to reasons of complexity and the lack of a mechanism to rank risks.

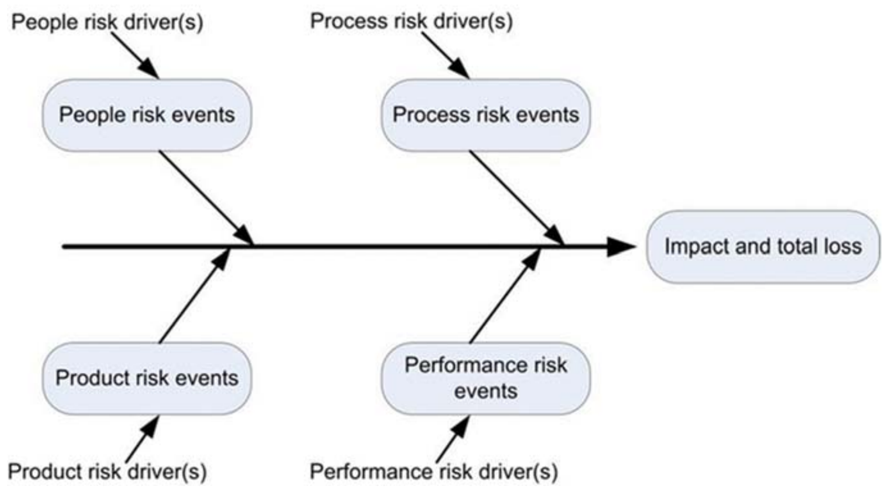


Figure 3-5: Ishikawa risk model (Smith and Merritt 2002)

3.3.1.5 Analytical Hierarchy Process

The Analytic Hierarchy Process (AHP) was developed by Thomas Saaty in the late 1970's to quantitatively assess qualitative criteria in the decision-making process. AHP utilizes a unique method of pairwise comparisons of alternatives with respect to a decision criterion to produce the quantities for ranking alternatives (Thibadeau 2007). Saaty advocated AHP for decision making when a complexity of goals and criteria are involved (Saaty 1991). One of the applications of AHP was conducted by Zayed, Amer and Pan (2008) who used the AHP as a component of risk management for a high-risk road construction project. In addition, Millet and Wedley (2002) surveyed prior research applying AHP in risk management and found applications in forestry and knowledge engineering, due to its strength in modeling uncertainty and deriving scales where measures ordinarily do not exist. Nevertheless, the paired comparison procedure of the AHP is not practical for the problem under study, or any application when there are many alternatives, since each alternative must be compared to all the other ones. In addition, the AHP process is inefficient in dealing with risks that can be ranked objectively, such as the expected loss in the Standard Risk Model or the RPN in FMEA. The process flow for AHP is shown in figure (3-6).

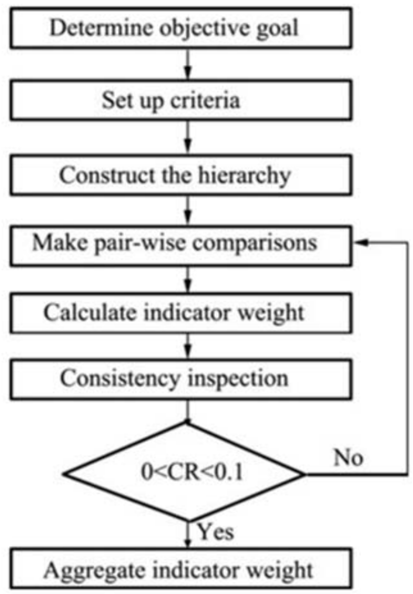


Figure 3-6: AHP process flow (S. Liu et al. 2013)

3.3.1.6 Fault Tree Analysis

Similar to the AHP, Fault Tree Analysis (FTA) seeks to quantitatively evaluate qualitative risk characteristics. In this model, each tree depicts a failure mode as interrelated gates with inputs at the bottom of the tree, passing upwards to outputs at the top of the tree. The symbols used to construct the trees are basic logic gate symbols that are understood in some disciplines such as electrical design (Vesely et al. 1981). FTA has been used in a variety of applications, including those in the aerospace (Stamatelatos et al. 2002), defense and automotive (Kabir 2017), nuclear power (Vesely et al. 1981), and tunneling (Hyun et al. 2015). One advantage of the FTA is that the probability computations involved in this model can take into account common causes of multiple failure modes (Stamatelatos et al. 2002). Furthermore, the use of “cut sets” can reveal the critical few components that contribute to vulnerabilities (Ruijters and Stoelinga 2015). On the other hand, Kabir (2017) notes two drawbacks of FTA. The first is that it applies only to static systems because it lacks structure for a time element. The second is that it is a manual process that is time consuming and expensive. Consequently, this drawback makes FTA impractical for the project under study as it will require an analysis of the cause and effect of blockages which are not universally agreed upon. An example of a fault tree applied to a medical risk is depicted in figure (3-7).

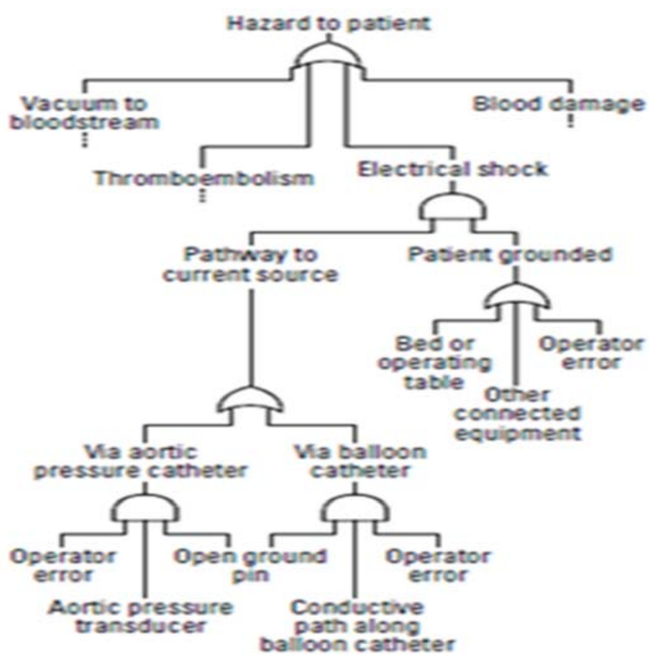


Figure 3-7: Example of a fault tree (S. Liu et al. 2013)

3.3.1.7 Failure Modes and Effects Analysis

Another commonly used model is the Failure Modes and Effects Analysis (FMEA) model. This model combines the risk probabilities and impacts into a single expected value number termed the “Risk Priority Number” (RPN). Selvik and Aven

(2011) suggest FMEA, or its variants, as an appropriate model in implementing the concepts of Reliability Centered Maintenance. Meanwhile, Liu et al. (2013) reviewed 75 papers on the subject of FMEA in an effort to summarize its shortcomings. They found that the most frequent shortcoming was the combination of risk rankings and occurrence rankings to produce a single RPN. The authors concluded that modifications to the traditional RPN calculation were effective, however, they added to the complexity of the model. FMEA is recommended as an appropriate risk model for the problem under study. A more exhaustive explanation of the FMEA methodology is provided in Section 4.1.

In conclusion, there is no single risk model that best fits every application and every organization must select the best model based on their needs. Karimiazari et al. (2011) named this process the "risk assessment model selection problem" and proposed a multi-criteria decision-making approach to select the best model.

3.3.2 Risk assessment of sewer systems

Several studies have approached the risk management of sewer pipe failure from the standpoint of expert judgement and pipe deterioration models. For instance, Mancuso et al. (2016) proposed a specific technique for prioritizing pipe inspections by utilizing expert judgement of the risks of failure and their severity. Johansen et al. (2007) proposed a similar technique by collecting expert opinions regarding the characteristics that lead to pipe failure. Another research effort that studied the risk of failure due to pipe deterioration was conducted by Salman (2010). In this research, the risk of failure due to pipe deterioration was assessed by utilizing the opinions of experts to qualify the consequences of failure combined with statistical deterioration modeling to quantify the probability of failure (Salman 2010). Furthermore, Salman's research cited 12 other studies using various methods and parameters to model sewer pipe deterioration. One of the cited studies is the one conducted by Sinha and McKim in 2007 who proposed a pipeline management system consisting of a standard pipeline rating system, a Markovian prediction model to forecast pipeline deterioration as a function of time, and a process to prioritize maintenance and rehabilitation based on cost. Salman also cites Ruwanpura and Ariaratnam (2003) who applied a rule-based Monte-Carlo simulation to predictive models of pipe structural conditions by using present condition, pipe age, type of material, and length of the pipe as inputs.

At the same time, few studies have explored the issue of modeling sewer pipe failure due to maintenance issues. The most conceptually similar study to the content of this research, albeit with different methodology, was the one conducted by Anbari et al. in 2017. After a comprehensive citing of prior research in sewer pipe failure the authors noted that the risk assessment procedure has not included the computation of the probability of failure (Anbari, Tabesh, and Roozbahani 2017). Another important study in this field was the one conducted by Arthur et al. in 2009 in which they recognized the importance of hydraulic failure, specifically blockage, in implementing a FMEA-based approach to risk prioritization. Finally, Berardi et al. (2009) included blockages as one objective in a three-objective optimization approach for risk assessment in sewer networks.

3.3.3 Risk threshold concept

One of the important constructs stressed by the Project Management Institute (PMI) is that an organization's risk attitude has a critical influence on how it responds to risks (Project Management Institute 2013). This attitude encompasses the organization’s risk appetite, risk tolerance, and the idea of a risk threshold that is adopted in this research. The PMI defines the risk threshold as a level of uncertainty or impact below which an organization will accept the risk and above which it will not tolerate the risk (Project Management Institute 2013).

Lempert and Collins (2007) viewed risk thresholds in three different concepts. The most straightforward concept is the use of optimum expected utility when uncertainty is well characterized and the cause-effect relationship is well understood. The second concept is the concept of precaution, which seeks to eliminate any risk above a threshold level. The third concept requires the understanding of the full range of uncertain outcomes with the probabilities associated with each and attempts to make decisions that are robust across all possible outcomes.

3.3.4 Multi-objective risk rankings

Other studies favored a multi-objective decision objective over the risk threshold concept. For example, Hafskjold et al. (2002) developed the Computer Aided Rehabilitation of Sewer Networks software application (CARE-S) to rank pipe rehabilitation candidates using multi-objective criteria. Furthermore, Berardi et al. (2009) set an objective of balancing economic, technical, and management objectives with a prioritization based on the number of times a particular pipe appeared in a multi-objective solution.

3.3.5 The role of monitoring and review

The 2009 International Standards Organization (ISO) document recognized the importance of ongoing monitoring and review in risk management which involves taking on new information about changing environments and understanding changes in the organizations' attitudes towards risk (Purdy 2010). In addition, Srinivasan and Parlikad (2013) recognized the value of condition monitoring to the general class of civil infrastructure. They advocated for the increased use of sensors to estimate condition and probability of failure of the sensors while cautioning that the key questions of what sensors to deploy, what value will the sensors provide, and how to use sensor data to make decisions must be answered.

Monitoring has been shown to be effective in similar applications. For example, the installation of continuous monitors in the grease disposal system at Children's Hospital in St.Petersburg, FL eliminated regulatory action and customer complaints, while also produced cost savings (Russell 2002). Another similar application was published by Montserrat et al. (2015) who analyzed data from continuous monitors placed in combined sewer overflows (CSO). The remote monitor data reported active CSO locations, which avoided the cost of sending inspectors to every overflow location after every rain event.

3.3.6 Common elements of modern risk management

A well-developed body of knowledge for risk management exists through the work of organizations such as PMI, ISO, and INCOSE. The common elements of modern risk management are the combination of risk probabilities and risk consequences into a framework that prioritizes or categorizes risk events for management attention. Modern risk management also incorporates the concept of a risk threshold by separating actively managed risks from acceptable risks and recognizes the important role of ongoing monitoring and review.

In the application of risk management to sewer pipe failure, the focus of researchers has been on finding methods to assess the probabilities of pipe failure, particularly structural failure modes. These methods rely on expert opinions and/or statistical models of pipe failure to predict future failure potential. In some cases, artificial neural networks have been employed to predict failure based on the different characteristics of the pipes and their environment (Moteleb and Salem 2010).

3.4 Conclusion

This chapter has investigated the state-of-the-art for managing sewage overflows due to blockage both in practice and in research. Preventative actions based on continuous monitoring is shown to be both more effective and more efficient than the prevailing practices of intervention based on complaint data, intervention based on inspection data, and interventions based on time since last intervention. Furthermore, the research in statistical models to predict blockage has not produced generally accepted techniques that are effective to be used across utilities. At best, the statistical models have predictive power within the collection systems that they were fit to. This leaves open the possibility that statistical models could be developed alongside continuous monitoring within particular collection systems. In addition, research into optimal sensor placement has not been applied to continuous monitoring for sewer blockage. In the fields where it has been applied, model-based approaches have been utilized to detect hypothetical failure scenarios. The limitations of sewer models and the lack of knowledge of actual failure scenarios make current research in sensor placement unsuitable for continuous monitoring in sewers. Based on the structure of the problem, a more promising approach is to apply one of the trajectory methods of metaheuristic search techniques with the goal of near-optimal placement of sewer level monitors. Finally, regarding risk management models, there has been no methodology proposed for ongoing monitoring as required by ISO 31000:2009 in relation to the problem of sewer blockages. Prior research has focused on predicting failures based on mathematical relationships between the pipe's characteristics and its environment. Furthermore, no prior research has attempted to assess the probabilities of failure using continuous monitoring, nor has any prior research dealt with the problem of where to place sensors to optimize risk assessment.

METHODOLOGY & RESULTS

The main objective of this chapter is to present the methodology implemented in this research to accomplish the goals and objectives. The implemented methodology comprises a number of different tasks, namely; 1) selecting an appropriate risk model for the sewage systems failure problem; 2) developing a realistic simulation to test location selection techniques through the adaptation of FMEA; 3) developing an algorithm to select a search technique and determine the optimum placement of sensors; and 4) design experiments to implement and validate the developed tool. In the following sections, the four tasks, together with how they were conducted, and the results obtained from them will be presented in detail.

4.1 Establishing a risk management framework

4.1.1 Selecting an appropriate risk model

The first goal of selecting a risk model is to choose the model that is, as Albert Einstein famously wrote, “as simple as possible and not simpler”. The simplest useful model would involve only the three common elements of a risk model, which are event probability, event consequences, and a measure combining the two. Other elements, such as risk drivers or risk probability distributions, were also considered in this research based on the potential extra value that they might add.

The second goal in selecting a risk model is to choose the one that is appropriate for the structure of the problem to be solved. Relative to risk management in other industries, such as construction, new product development, or financial portfolio management, the issues studied in this research are relatively straightforward. Since, in this research, the risk management principles are applied to a question of infrastructure asset maintenance, it is not necessary to identify a wide range of risk drivers, such as the people risk, process risk, product risk, and performance risk incorporated in the Ishikawa risk model (Smith and Merritt 2002). Moreover, it is not particularly valuable to examine possible outcomes on the full spectrum of possible risk probabilities and consequences, such as methods employing Monte Carlo simulation (Project Management Institute 2013).

Failure Modes and Effects Analysis (FMEA) was determined to meet the above criteria for simplicity and suitability to the problem at hand. In the variant proposed, FMEA utilizes only the three common risk model components. Furthermore, prior research has documented the successful application of FMEA to manage preventative maintenance activities (Braaksma, Klingenberg and Veldman 2013).

It should be noted that the risk assessment techniques presented in this research do not necessarily depend on the risk model selected. The application of metaheuristic search techniques to select efficient locations for continuous monitoring can serve as risk probability inputs to a variety of risk management models.

4.1.2 Implementation of Failure Modes and Effects Analysis

FMEA was first developed as a tool for product design in the aerospace industry in the 1960’s where reliability and safety were critical design priorities (Bowles and Enrique Peldez 1995). The procedure first involves identifying all potential failure modes of a system or process. Then, for each potential failure, a risk priority number (RPN) is calculated as the product of a risk occurrence rating (O), a risk severity rating (S) and a rating for detectability (D).

$$RPN = O*S*D \tag{4-1}$$

In traditional FMEA, the ratings for each element of the RPN is normalized on a scale of 1-10, where the interpretation of the numbers of the scale are left open to assignment by the practitioner and do not have to be linear. For example, a risk occurrence rating of 8 does not necessarily mean a quantified risk that is double that of a risk occurrence rating of 4. Moreover, ratings for O, S, and D can be qualitative or quantitative. This is particularly common for severity ratings where a rank of 1 might indicate “no ill effect” and 10 might indicate “failure is hazardous and occurs without warning”. Ratings for detectability are also commonly qualitative, ranging from low ranks that indicate that the detection is “almost certain”, to high ranks indicating that the detection is “absolutely uncertain”.

This method produces RPN values ranging from 1 to 1,000. In the case of the latter occurrence, severity and detectability will all be at their maximum value of 10. Consequently, higher RPN number indicates higher risk, thus demanding the highest attention (Liu et al. 2013).

4.1.3 Adaptations of traditional FMEA in this research

4.1.3.1 Estimating risk severity score

Although it is not the purpose of this research to develop a severity scoring methodology nor is a novel methodology necessary for the framework proposed in this research, the only necessary condition required for this research is that the evaluator assign severity scores that can be standardized on a scale between 1 and 10. To achieve this standardization, a method was defined that involved creating a scoring rubric and assigning these scores to sewer pipe locations through a satellite imagery analysis procedure. This method is consistent with EPA guidance which took into consideration several factors that were simple to implement.

The factors that were considered before designing this method came mainly from two sources: the EPA combined sewer overflows guidance for screening and ranking, and the EPA report to Congress on the impacts and controls of CSO’s and SSO’s. Regarding the former, EPA prioritizes controlling overflows to sensitive areas. These areas include designated Outstanding National Resource Waters, National Marine Sanctuaries, waters with threatened and endangered species and their habitat, waters with primary contact recreation, pubic drinking water intakes or their designated protection areas, and shellfish beds. Figure (4-1) is a compilation of the ranking criteria in the EPA’s report organized by risk severity scores assigned by the author. The scores are based on standardizing the EPA point scale of 0-250 to a 10-point scale and are rounded to the nearest integer. Shaded boxes were used for cross reference to the EPA scoring system. Unshaded boxes were considered but not used as input for the study methodology due to the difficulty in obtaining information on the scale of a sanitary sewer system.

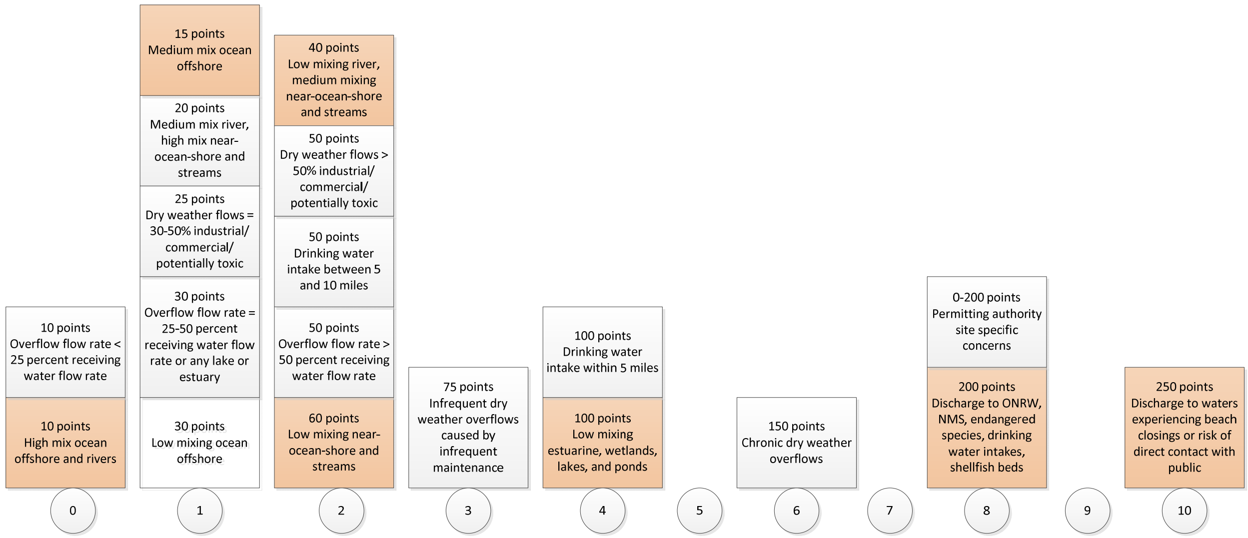


Figure 4-1: Standardized consequence rating based on point assignments

Regarding the latter source, this report divided the impacts into two broad categories: environmental impacts and human health impacts. Although a scoring scale was not provided (US EPA 2004a), it can be inferred that the foundation of a severity scoring process would be based on the five designated water uses potentially compromised by sewer failure and the impact of human health. The five designated uses that are potentially impacted by sewer overflows are:

1. Aquatic life support
2. Drinking water supply
3. Fish consumption
4. Shellfish harvesting
5. Recreation (e.g. swimming, boating)

This report influenced the severity ratings used in this research by assigning the highest severity scores to potential overflow locations (manholes) that were near waterways. Higher severity ratings were also assigned in this research to locations where overflows present higher jeopardy for humans to come into contact with wastewater and thus risk human health.

Two other notable sources contributed to the development of this method. Bowles & Enrique-Peldez (1995) reserved the lowest scores for failures that are so minor that they may not be noticed, mid-range scores for failures that produce customer dissatisfaction and noticeable impaired performance, and highest severity scores for those that affect safety or violate government regulations. Arthur et al. (2009) attempted to evaluate the overflow consequences based on the following factors:

1. The level of deprivation of the population affected by the overflow.
2. Recurrence of the overflows.
3. Land use: The highest severity ratings were for protected land areas and urbanized land areas. Waterways were assigned the next highest ratings followed by industrial land areas. Particularly vulnerable areas, such as schools and hospitals, were assigned higher severity ratings, while shopping areas also received special consideration.
4. Road usage.

4.1.3.1.1 Create a scoring rubric

The scoring rubric created for this research is shown in table (4-1). Scores were scaled from 1 to 10, consistent with FMEA. In the first column of the table, FMEA qualitative terms are included, ranging from “minor” to “highest” severity. The second column contains a qualitative description of the worst consequence that could reasonably occur if a failure were to happen at a location. The concept of “worst consequence” is discussed below. The third column, GIS Indicators, are the visible indicators of areas that are prone to the consequences of each line in the rubric. This linkage simplified the rating process to an analysis of satellite imagery. The last column cross references each rating to EPA guidance to support the relative rankings. The intention of this cross reference was to be as consistent as possible at least with the rank order of potential impacts.

Table 4-1: Risk severity scoring rubric

Score/FMEA Description	The worst consequence in case of overflow	GIS Indicators	Cross Reference to EPA Guidance
1 Minor	Overflow unlikely to be noticed or to cause ecological damage	Unpopulated/untraveled areas such as forests and fields	Discharge to rapidly mixing ocean offshore 10
2 Minor +	Loss of enjoyment due to odor or visible sewage – low population density	In the vicinity of populated areas but not in direct contact with the public. In areas where sewage could be visible such as beside roadways.	Discharge to medium mixing ocean offshore 15
3 Low	Loss of enjoyment due to odor or visible sewage – high population density	In the vicinity of populated areas but not in direct contact with the public. In areas where sewage could be visible such as beside roadways.	Discharge to streams, rivers, and near-shore oceanic 40-60
4 Low +	Traffic disruption	Near roadways where street flooding is possible	Discharge to estuarine and wetland, lakes, and ponds. Tourism affected. 100
5 Moderate	Aquatic life support compromised - minor	Near minor estuaries, wetlands, lakes, ponds	Discharge to estuarine and wetland, lakes, and ponds. Tourism affected. 100
6 Moderate +	Aquatic life support compromised - major	Near major estuaries, wetlands, lakes, ponds	Discharges to national resource waters, sanctuaries, threatening endangered species. -200/Aquatic life support, meaning

Score/FMEA Description	The worst consequence in case of overflow	GIS Indicators	Cross Reference to EPA Guidance
			the water provides suitable habitat for the protection and propagation of desirable fish, shellfish, and other aquatic organisms.
7 High	Public health compromised through drinking water or consumable fish supplies	Near public drinking water intakes or fishable bodies of water including shellfish beds	Discharges to public drinking water intakes, or shellfish beds -200 /Drinking water supply, meaning the water can supply safe drinking water with conventional treatment…Fish consumption, meaning the water supports fish free from contamination that could pose a significant human health risk…Shellfish harvesting, meaning the water supports a population of shellfish free from toxics and pathogens that could pose a significant health risk to consumers.
8 High +	Public health compromised through surface contact – suburban	Near occupied structures or public outdoor areas including residential, industrial, and commercial buildings and public parks in areas such as sub-divisions, highway rest areas, small industrial parks	Discharge in streets or basements -250 (direct contact with public)
9 Very High	Public health compromised	Near occupied structures or public outdoor areas including	Discharge in streets or basements -250

Score/FMEA Description	The worst consequence in case of overflow	GIS Indicators	Cross Reference to EPA Guidance
	through surface contact - urban	residential, industrial, and commercial buildings and public parks in densely populated areas with multi-family dwellings, schools, hospitals, shopping malls	(direct contact with public)
10 Highest	Public health compromised through water contact	Near swimmable waters	Discharges to waters experiencing beach closings or where there is significant risk to public health from direct contact with pollutants – 250 (Note: Normalized - 250 to 10)//Recreation, meaning water-based activities (e.g., swimming, boating) can be performed without risk of adverse human health effects

4.1.3.1.2. Satellite imagery analysis procedure

The use of GIS indicators allowed the severity scores to be easily assigned using a GIS database containing the location of sewer pipes and manholes, overlaid on a base map of satellite imagery or aerial photography. Pipes were selected by drawing polygons around areas of equal severity rating in accordance with the scoring rubric. A severity field was created in the GIS database to store the ratings.

An example of a small section of aerial photography is shown in figure (4-2) below. Pipes colored green are low severity scores in the range of 1-3 because they are in unoccupied land areas not near waterways, pipes colored yellow are of a severity score of 8 because they are in neighborhoods, while pipes colored red are of a severity score of 9 because they are near more densely populated structures in an industrial park.

Figure 4-2: Example of the satellite imagery analysis procedure

4.1.3.1.3 Limitations of severity ratings based on total loss assessments

The severity rating method used in this research assigned severity scores based on a worst outcome scenario. The standard risk model and FMEA do not provide a mechanism for probabilistic impacts of risk events. For example, a failed pipe, defined in this study as a surcharged pipe, may not result in any measurable impact if the surcharge wastewater volume is contained within the collection system (e.g. within manholes). Similarly, a short-duration overflow would result in less severe impacts than a very long one, all other variables being equal. No data currently exists to formulate probability distributions for failure consequences. This is another potential benefit of the data that would be obtained through systematic level monitoring as proposed in this research.

4.1.3.2 Estimating risk occurrence score

The first step of this estimating the risk occurrence score was to consolidate and organize depth-duration frequency data which was then followed by an exploratory data analysis. This analysis led to the choice of a binary logistic regression approach. Based on diagnostic data from this regression, a further step was introduced to associate the output of binary logistic regression with the observed probability of pipe surcharge.

4.*1.3.2.1 Source of data*

The data came from a sample of level sensor data from 456 monitoring sites (manholes) from seven different sewer systems in the United States. Sensors containing ultrasonic level and pressure depth transducers were installed inside the upstream pipes of manholes at the locations. The sensors were connected to battery powered monitor units with wireless telemetry. The monitor acquired and stored measurements on 5-15-minute sample rates. Data was transmitted to a central database at least once each day. The configuration of a typical installation is shown figure (4-3).

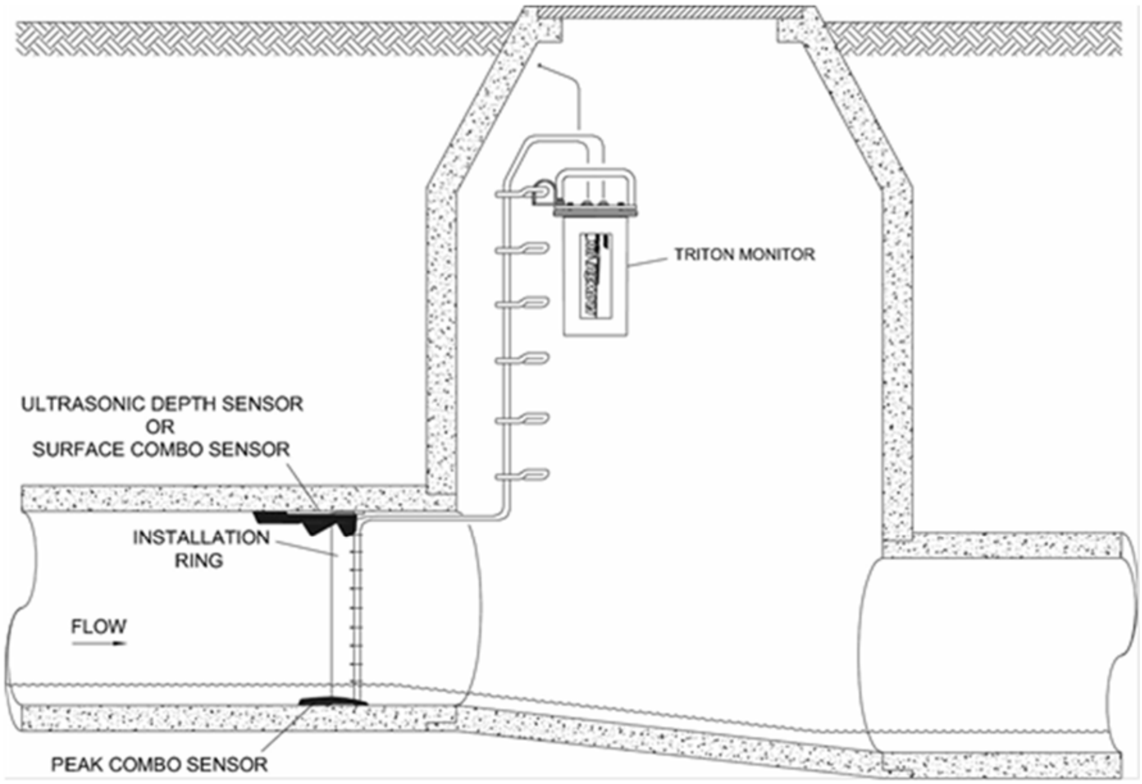


Figure 4-3: Configuration of a typical monitor installation

The data encompassed the period from 1 September 2017 to 1 October 2017. The sample data is from a wide range of pipe sizes with the smallest being a 4-inch diameter pipe and the largest being a 120-inch pipe. The plot in figure (4-4) shows the distribution of the 456 sites by pipe height.

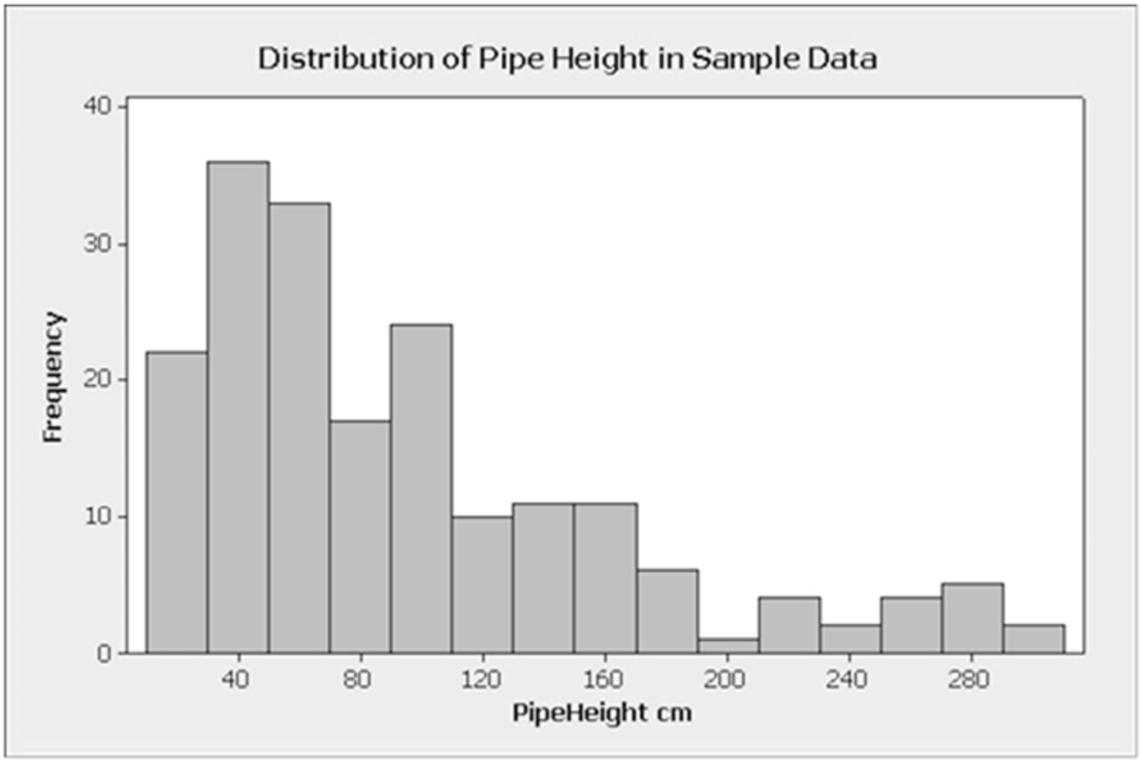


Figure 4-4: Distribution of sites by pipe height

4.1.3.2.1 Construction of depth-duration frequencies

The 456 sampled sites were divided into two sets: a set of 416 sites was selected for model fitting and a set of 40 sites was used as a test data set. There were 59 sites that surcharged in the training data set (14.2%) whereas five sites surcharged in the test data set (12.5%). A hypothesis test of the two surcharge proportions shows a high possibility that the differences in the proportions between the two sets are due to chance (p-value of 0.76). Therefore, we fail to reject the null hypothesis that the two surcharge proportions are the same.

An R-script was written to consolidate the time series data consisting of time-stamped level measurements. Most sites were sampled every 5 minutes for a total of 1,994,713 individual time-stamped measurements in the data set. Each measurement was then divided by its pipe diameter to normalize the water level measurement to a proportion of full pipe, commonly referred to as the d/D (depth-to-diameter) ratio. The calculated d/D was rounded to the nearest tenth with all d/D values greater than or equal to 1 rounded down to 1. This produced 11 unique values of d/D for each location in the range 0.0, 0.1, 0.2 …1.0. A binary categorical variable was created to tag all sites that experienced surcharge (d/D >= 1) at least once during the sample period.

Next, the proportion of readings observed at each d/D value bin for each site was calculated. From this it was possible to construct d/D frequency polygons for each site. The selection of frequency polygons as a graphical device was due to their ability to facilitate the comparison of multiple distributions on a single chart. From the frequency polygons, cumulative frequency polygons (ogives) could be easily created. An Ogive Graph from 5 monitoring sites from the database is shown in figure (4-5). The lines are interpreted as the proportion of observations (measurements) at or below the d/D bin on the x-axis.

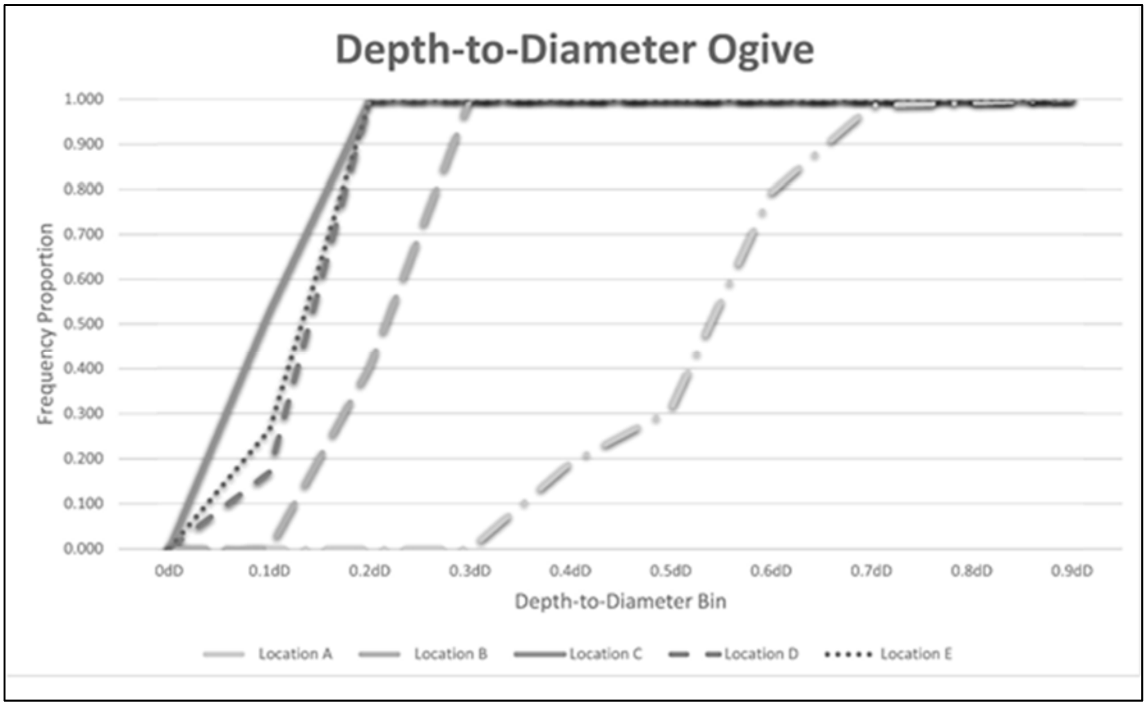


Figure 4-5: Ogive graph from 5 monitoring sites

The building blocks of the d/D frequency polygons are the same as those used to construct depth-duration curves commonly used in hydrology to depict the proportion of time a stream exceeds certain flow rates or water levels. In the case of sewer pipes, a case can be made that available capacity is of greater importance than the flow rate or water level since any flow quantity is acceptable so long as it can be accommodated by pipe capacity. This is another motivation for selecting ogives as the default visualization of flow properties.

4.1.3.2.2 Exploratory data analysis of d/D frequencies

An exploratory data analysis was performed on the data comparing sites that experienced surcharge with those that did not. The interval plot in figure (4-6) shows that the differences in the mean of surcharge versus non-surcharged sites are statistically significant (alpha = 0.05) in the smallest and largest d/D bins. The mean frequency of readings of non-surcharged sites is significantly above that of surcharged sites in the 0.0 d/D, 0.1 d/D, and 0.2 d/D bins. Conversely, the mean frequency of readings in surcharged sites is significantly above that of non-surcharged sites in the 0.7 d/D, 0.8 d/D, and 0.9 d/D bins. The case of 1.0 d/D is special because, by definition, any readings at this level are classified as surcharge. The mean frequency of readings is not statistically different in the middle range of bins above 0.2 d/D and below 0.7 d/D. An inference from this analysis is that a comparison of depth-duration frequency data in the lowest and highest d/D ranges might be predictive of whether or not a site will go into surcharge.

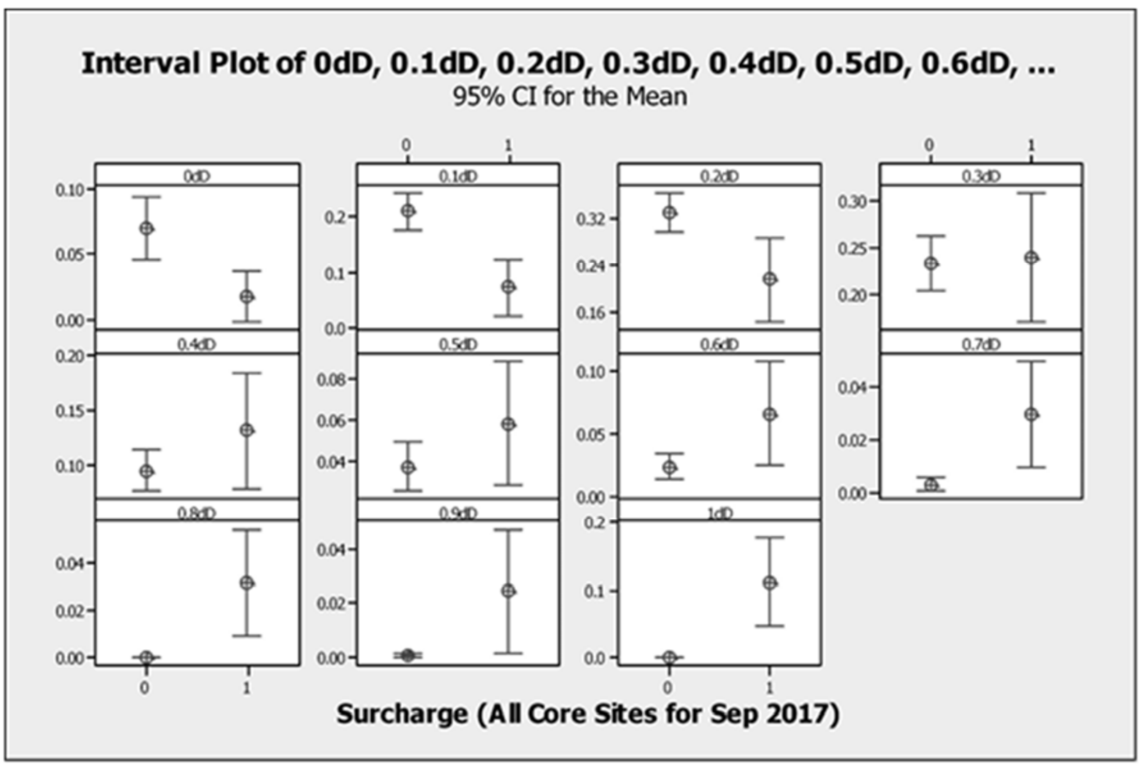


Figure 4-6: Interval plot

4.1.3.2.3 Statistical model development and diagnostics

Since the objective of this study is to predict which pipes will enter a surcharge state based on data obtained when the pipe is in a non-surcharged state (e.g. free carrying capacity > 0) the 1.0 d/D bin was excluded from consideration as a predictor.

4.1.3.2.3.1 Binary logistic regression

The problem presented has a simple structure that lends itself well to a binary logistic regression model. The ten d/D bins are predictor variables. Each predictor takes on a value between 0 and 1 representing a proportion and the sum of these proportions must equal 1 for each observation (each monitored location). The surcharge state is the lone dependent variable. There are only two possible states. Thus, it is straightforward to assign a value of 0 to observations where no instances of surcharge were recorded and 1 to observations that entered the surcharge state 1 or more times.

Consequently, since binary logistic regression is a statistical model designed for this type of problem with continuous predictor variables and a binary response variable, the model is stated in terms of the probability that the response variable, Y, is equal to 1, given predictor variables X in the form:

$$\mathrm{Prob}\{Y=1|X\} = [1+\exp(-\beta X)]-1 \qquad (4\text{-}2)$$

where $\beta X = \beta 0+\beta 1X1+\beta 2X2+\ldots+\beta kXk$

The regression parameters β are estimated by the method of maximum likelihood (Harrell 2015). At each stage of modelling, the model was analyzed to assure that it met the assumptions of binary logistic regression as outlined in the Laerd Statistics guidance through the use of the following criteria (Laerd Statistics 2017):

1. The dependent variable should consist of two categorical, independent groups (i.e., a dichotomous variable). This assumption was met by the dependent variable being a state variable represented by 0 and 1.
2. There exists one or more independent variables that are continuous or nominal. This assumption was met by the fact that all of the independent variables are continuous across the range of 0-1. In the final model there were two predictor variables and one constant.
3. The observations are independent. The observations were selected from monitoring sites chosen in 7 different systems in geographically separated locations. The independence of the observations was tested with a cross correlation test described in assumption #4 below.
4. There should be no collinearity between independent variables. Cross correlation was tested between all possible independent variables. In some cases, this analysis indicated the potential for collinearity. Hence, highly correlated variables were excluded from the final model. The Pearson correlation of the two independent variables in the final model was 0.086 and 0.079. An alpha level of 0.10 was used to accept the independence of the variables.
5. There is a linear relationship between the continuous independent variables and the logit transformation of the dependent variable. This was tested by conducting a least-squares linear regression using a logit transformation of the binary dependent variable (surcharge) and the untransformed values of the 0.7 d/D and 0.1 d/D continuous independent

variables. The p-value of the regression was 0.000 which indicated that the regression coefficients were significantly different from zero and therefore a linear relationship was justified.

6. There should be no outliers, high leverage values or highly influential observations that would skew the regression model. The graphs of outliers based on probability and leverage indicated 2 outliers in the data as shown in figure (4-7). The model was tested by removing the outliers from the data set and recalculating the regression. The test showed that the model did not materially change. Therefore, the observations were allowed to remain.

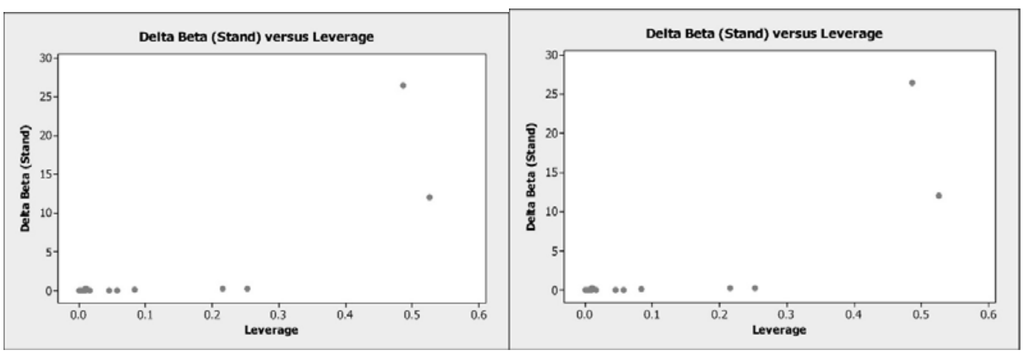


Figure 4-7: Probability & leverage graphs

4.1.3.2.3.1.1 Fitting the binary logistic regression model

Binary logistic models were developed using a generalized linear model. Three link functions were explored - the inverse of the cumulative logistic distribution function (logit), the inverse of the cumulative standard normal distribution function (normit), and the inverse of the Gompertz distribution function (gompit). The three functions produced near identical goodness-of-fit statistics. The logit link function had one significant benefit in providing estimates of the odds ratio for each predictor in the model. Therefore, the logit link function was selected for use in both software applications.

In the first iterations of model development, all ten predictors from 0.0 d/D to 0.9 d/D were available. The state variable, whether or not the site was observed in surcharge in the sample period, took on a value of either zero (no surcharge) or 1 (at least one observation in surcharge conditions). Collinearity was a problem when including all predictor variables. Hence, terms were systematically removed from the model one at a time based on the p-value of the coefficients in the regression output until all terms were at a p-value below the alpha level of 0.05.

After constructing a model using the frequencies of observations in each depth bin, another model was constructed using cumulative frequency data in each bin. The model based on cumulative data produced slightly better diagnostic data with a log-likelihood of -139 versus -140 for the non-cumulative data and a Somers D measure of 0.58 versus 0.57. In a few cases the cumulative data model yielded predicted event probabilities that seemed more reasonable than the non-cumulative model. Based on these slight differences the cumulative data model was chosen. In practical terms the two models produced indistinguishable results and the use of either would be equally valid.

Finally, the final binary logistics regression model was tested against the six assumptions of binary logistic regression to insure none of them were violated. Moreover, the addition of an interaction term to the final model was tested, but this did not improve the goodness-of-fit. Consequently, it was removed.

4.1.3.2.3.1.2 Estimating FMEA failure probabilities from binary logistic regression predicted event probabilities

The event probability in the context of this study is the likelihood that a monitor location would enter a surcharged state at least once in a 30-day period given the data observed in the 0.1 d/D and 0.7 d/D bins. In general, the greater proportion of measurements in the bins above 0.7, the greater the chance of surcharge.

FMEA requires an assessment of failure occurrence probabilities on a 1-10 risk scale. While general guidelines exist for the risk ranking scales, the principle is that it is important to tailor the risk ranking scales to organization-specific applications (H.-C. Liu, Liu, and Liu 2013). Thus, for this study, the organization-specific application was to devise a risk scale that reflected the observed frequency of surcharge in the available data. For example, a risk rank score of 10 would suggests a near 100% chance of surcharge, a 9 would suggest approximately 90% chance of surcharge…etc.

Consequently, to calibrate the binary logistic regression event probabilities to FMEA risk ranking, all 456 monitoring locations were considered. For each location, the binary logistic regression event probabilities were calculated, and the data was then summarized to two significant digits of the event probabilities and compared to the actual proportion of surcharged locations. A curve was fit using the prediction probabilities as the independent variable and the observed probabilities as the dependent variable. Finally, outliers were removed from the data where there were very few observations at particular event probabilities.

Based on the above, a Morgan-Mercer-Flodin growth model provided a reasonable approximation of observed surcharge proportions based on binary logistic regression event probability inputs. The approximated surcharged proportions were then multiplied by 10 to arrive at the 1-10 risk scale appropriate for FMEA risk rankings.

4.1.3.2.3.2 Statistical modeling results

Results are presented for the binary logistic model, the MMF growth model, and the consolidation of the two models.

4.1.3.2.3.2.1 Binary logistic regression model equation

Selected output from the binary logistic regression is shown in table (4-2) below.

Table 4-2: Selected output from the binary logistic regression

Predictor	**Coefficient**	**P-Value**	**Odds Ratio**
Constant	24.4413	0.026	
0.1dD	-1.59969	0.007	0.20
0.7dD	-26.1789	0.017	0.00
Test that all slopes are zero p-value: 0.000			

Since the logit link function was employed the equation for the model is in the form:

$$\ln\left(\frac{p}{1-p}\right) = 24.4413 - 1.59969(0.1dD) - 26.1789(0.7dD), \text{ which is:}$$

$$\text{Probability of event, } p = \frac{e^{24.4413-1.59969(0.1dD)-26.1789(0.7dD)}}{1+e^{24.4413-1.59969(0.1dD)-26.1789(0.7dD)}} \text{ where,} \quad (4\text{-}3)$$

1. An “event” is a monitor location where a pipe surcharge was recorded at least once during the 30-day sample of level measurements.
2. 0.1dD and 0.7dD are the cumulative proportion of sensor measurements at the 0.1 depth/diameter bin and the 0.7 depth/diameter bin.

4.1.3.2.3.2.2 Statistical significance

The p-value for the test that all slopes are zero is less than the chosen alpha value of 0.05 indicating there is a significant association between at least one predictor variable and the response. Likewise, the p-values for the three predictors are less than

0.05 indicating that each of them has a statistically significant association with the binary outcome variable (e.g. surcharge).

4.1.3.2.3.2.3 Interpretation

Since both predictors are continuous variables, the coefficients are the estimated change in the natural log of the odds for the event for each unit increase in the predictor. Because the 0.1dD and 0.7dD predictors are proportions ranging from 0 to 1, a unit increase would be a predictor value increasing from 0 (no observations at that depth or below) to 1 (all observations at that depth or below). Table (4-3) shows the changes in the log odds and probabilities of the surcharge event for 1-unit changes in the predictors. Increases in either the 0.1dD or the 0.7dD proportions result in lower probabilities of surcharge.

Table 4-3: Changes in the log odds and probabilities of the surcharge event

0.1dD Proportion	0.7dD Proportion	Log odds	Estimated probability of surcharge event	Interpretation
0	0	24.4413	1.000	All measurements must be above 0.7dD therefore the probability of surcharge is very high
0	1	-1.7376	0.150	All measurements are 0.7dD or below therefore probability of surcharge is low
1	0			This is an impossible reading using cumulative data
1	1	-3.3373	0.034	All measurements are 0.1dD or below therefore probability of surcharge is very low
		-26.179	-0.8503	Change when 0.7dD moves from 0 to 1
		-1.600	-0.1153	Change when 0.1dD moves from 0 to 1

The coefficients and odds ratios indicate that the probability of a surcharge event vary inversely with the proportion of readings at 0.1dD and 0.7dD. The estimated probabilities of the surcharge event are much more sensitive to changes at the 0.7dD level than at the 0.1dD level.

It may seem counterintuitive that more observations at the 0.7dD level lead to a decrease in the probabilities of the locations experiencing surcharge. The explanation lies in the use of cumulative frequency data. Higher proportions of readings in the 0.7dD and below levels equate to fewer readings above 0.7dD. This suggests that the critical water level in wastewater pipes is the area above 70% full. When water levels are in this area even for small proportions of time, the risk of surcharge escalates rapidly.

One explanation for the sensitivity of pipes at 0.7dD is the geometry of circular pipes. Once a circular pipe is past half full, the carrying capacity diminishes rapidly. At 0.7dD the cross-sectional area of the pipe is 75% full. Its design capacity as given by Manning's equation is 84% used.

Compounding pipe geometry is empirical evidence that many pipes are not capable of conveying their design capacity. In a separate sample of 141 flow monitor sites that exhibited surcharge, only 16% of the sites carried their design capacity when full, with the mean of 76% of design capacity when full (see Appendix A).

4.1.3.2.3.2.4 Goodness-of-fit of binary logistic regression model

Five Chi-Square goodness-of-fit tests were performed to assess how well the binary logistic regression model predicted the actual outcomes in the data. The outcomes were mixed as shown in table (4-4) by the contrasted p-values of the various tests. Tests with p-values below the chosen alpha value of 0.05 are considered failed tests.

Table 4-4: Goodness of fit test outcomes

Method	Chi-Square	Deg. Freedom	P-value	Interpretation
Pearson	381	260	0.000	Reject
Deviance	252	260	0.631	Do not reject
Hosmer-Lemeshow	72	6	0.000	Reject
Brown General Alternative	5	2	0.097	Do not reject
Brown Symmetric Alternative	~0	1	0.783	Do not reject

Further analysis into the goodness-of-fit indicates that there are types of large residuals not predicted well by the model. The weight of these outliers varies depending on the test. This is one explanation as to why the model is rejected by some tests and not others. The chart in figure (4-8) shows rounded predicted event probabilities from the binary logistic regression on the x-axis versus the observed proportion of sites that actually surcharged in the data sample.

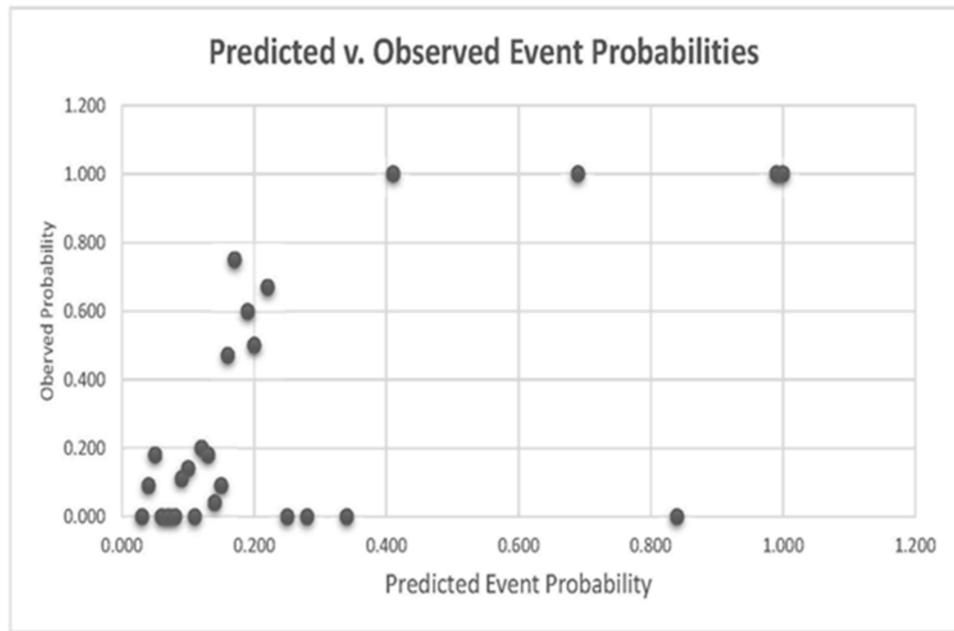


Figure 4-8: Rounded predicted event probabilities

The graph suggests the potential for a pattern of association in the scatterplot. However, it is clearly not a straight line beyond approximately 0.20 on the x-axis and there are obvious outliers. It is worthwhile to note that each point between 0.20 and 0.90 on the x-axis is a proportion where the number of observations in each is less than n=5. The confidence intervals for observations in this range are very large.

The conclusion regarding goodness-of-fit is that the model is clearly not a perfect representation of reality. This comes as no surprise given the limited number of predictors and short time sample. Despite being rejected by 2 of 5 tests, the binary logistic model can still be useful for prediction based on the measures of association discussed below. More importantly, the additional modeling performed to derive FMEA risk rankings improved the fit of the final results.

4.1.3.2.3.2.5 Measures of association of binary logistic regression model

For the primary objective of this study, predicting relative risk of surcharge, the measures of association are the most critical diagnostics. The data from 40 monitoring locations was held out of the data used to calculate the binary logistic regression model for the purpose of testing. In these 40 sites there were 5 surcharge events. Of these 5 sites with events, 4 were in the top 5 highest predicted event probabilities using the model.

There was only one site with a false negative, a low predicted event probability that surcharged. This was a very unusual depth pattern where near 100% of readings were at the 0.2dD level and below except for very rare and short surcharge observations, which may be the result of erroneous data or an unusually rapid loss of capacity. The output of the measures of association for the training data set is shown in table (4-5).

Table 4-5: Measures of association for the training data set

Measures of Association (Between the Response Variable and Predicted Probabilities)				
Pairs	**Number**	**Percent**	**Summary Measures**	
Concordant	15,995	77.2	Somers D	0.59
Discordant	3,750	18.1	Goodman-Kruskal Gamma	0.62
Ties	961	4.6	Kendall's Tau-a	0.14
Total	20,706	100		

The measures of association pairs each observed surcharge location to every other non-surcharge location. If the surcharged location has a higher predicted probability, then that pair is classified as concordant. Otherwise it is discordant. Using the binary logistic regression model over 77% of the pairs were concordant. Somers D and Goodman-Kruskal tests are simply ratios of concordant pairs to the discordant or total pairs calculations. Higher numbers indicate stronger predictive capability of the model.

For risk priorities in FMEA these are important conclusions as to the value of the binary logistic regression model. The main objective of the FMEA in this study is to locate sensors in the highest risk locations meaning that ranking of risk is the actionable information, and lack of fit suggests that the model will not give realistic surcharge probability estimates over the full range of data, the measures of association indicate that it can provide appropriate rankings of risky locations with near 80% accuracy.

4.1.3.2.4 Estimating FMEA risk rankings based on predicted event probabilities

A final step was added for the purposes of; a) improving the fit of the model, and b) deriving FMEA risk rankings in the range of 1-10 that approximate the observed probabilities of surcharge in the data. This adds meaning to the risk ranking scores beyond just a relative ranking.

An MMF growth curve proved to be a good fit between the independent variable of predicted event probabilities and the dependent variable of observed surcharge probabilities in the full data set. The fitted curve is symbolized by the gray line in figure (4-9) below.

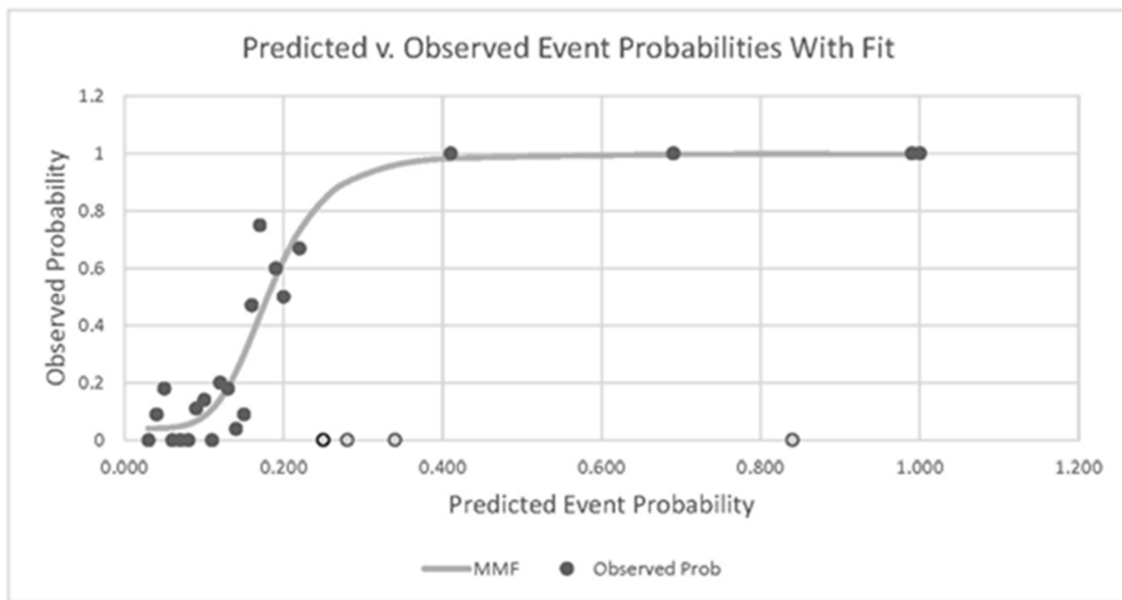


Figure 4-9: MMF growth curve

4.1.3.2.4.1 Data conditioning

The four observations shown in grey each contain fewer than 5 observations with very large confidence intervals such that much better fits to the MMF curve cannot be ruled out with more data. Therefore, those observations were removed for the computation of diagnostics.

4.1.3.2.4.2 Diagnostics

The coefficient of determination (r^2) for the MMF curve is 0.92 indicating a good fit. The p-value of the residuals is 0.067 which allows the conclusion that a run pattern of the residuals is unlikely at an alpha level of 0.10. The data, excluding points with small sample size, fit within the 90% prediction intervals of the fitted curve.

The final FMEA risk rankings were computed by rounding the predicted observed probabilities from the MMF curve equation to the nearest integer. This resulted in risk scores between 1 and 10. Combining the binary logistic regression model and the MMF growth model fitted curve produced a consolidated formula to calculate FMEA risk rankings directly from monitor data as follows where x is the 0.1dD cumulative frequency and y is the 0.7dD cumulative frequency.

$$\frac{0.000007 + 0.9969\left(\dfrac{2.718282^{24.4413 - 1.59969x - 26.1789y}}{1 + 2.718282^{24.4413 - 1.59969x - 26.1789y}}\right)^{5.10679}}{0.00017 + \left(\dfrac{2.718282^{24.4413 - 1.59969x - 26.1789y}}{1 + 2.718282^{24.4413 - 1.59969x - 26.1789y}}\right)^{5.10679}} \quad (10)$$

(4-4)

Two visualizations illustrate the fit of the combined models. Figure (4-10) shows the final scores plotted on the x-axis and the observed proportion of overflows for each score. No plot is shown for scores of 8 or 9 because there was only one observation of each in the data. The fit is very close to a straight line through the origin meaning that a score of 1 corresponds to a ~10% probability of surcharge, a score of 6 corresponds to a ~60% probability of surcharge, etc. However, the residuals around the scores of 2,3, and 4 are worrisome as they highlight the sensitivity of the mathematical models in this region. The residuals are considered acceptable since the highest risk categories (above 5) are the ones of most interest. The r^2 value of 0.82 indicates an adequate fit.

Figure 4-10: The fit of the final scores

The relationship of scores and the raw measurement data can be visualized in figure (4-11) below. The x-axis represents all of the depth bins used to record non-surcharge data, while the y-axis depicts the proportion of observations for the given depth bins. This data is not cumulative to highlight the differences in shapes of the frequency data.

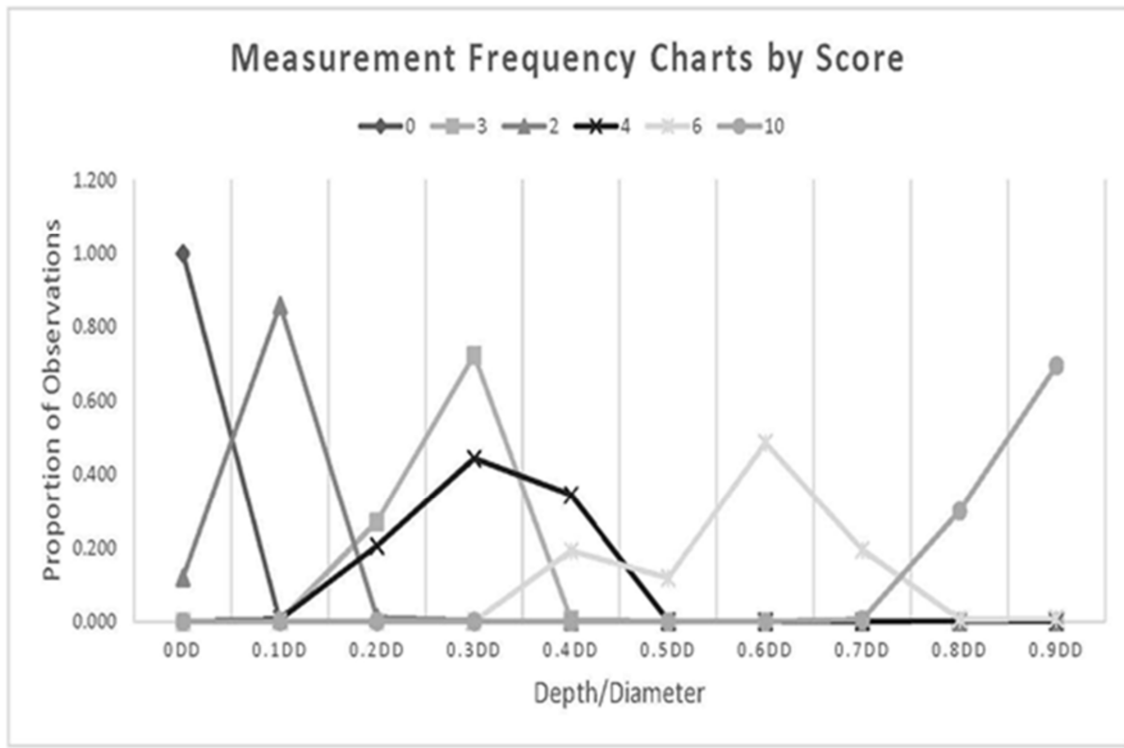


Figure 4-11: The relationship of scores and the raw measurement data

Each line on the chart is a monitor location with a different FMEA risk ranking score. It is evident that higher scores are assigned to monitor locations that have more level measurements in the higher depths as expected. It is interesting to observe the highest risk score, 10, is given to a location that has zero observations in bins at or below 0.7 dD providing further evidence of the sensitivity of the 0.7 dD bin.

4.1.3.2.5 Conclusions of risk occurrence rating methodology

Useful FMEA risk rankings can be estimated using only level monitor data for short periods, in this case 30 days. Compromises in goodness-of-fit and association still permit risk prediction accuracy near 80% with only 30 days of monitoring.

More research is needed to determine the optimal time period of data to produce risk rankings. The shorter the time for monitoring, the more locations that can be assessed for risk within a given monitoring program budget and schedule. Consequently, with more locations, the odds of finding the highest risk areas are increased so that actions can be taken to prevent the release of sewage into the environment.

4.1.3.3 Ignore detectability in RPN calculations

The concept of detectability is important in managing risk. The purpose of the detection rating is to estimate how well controls that are currently in place will detect a failure or a potential failure after it has happened yet before the customer is affected (American Society for Quality 2018). In this research, risk modeling both with and without detectability ratings were first considered. It was concluded that the process is made simpler by accounting for detectability in the active management activity rather than in the risk assessment activity.

For the case of sewer pipelines, controls exist if a continuous monitoring device is installed in a location. It is also recognizable that differing frequencies of manual inspection provide better levels of detectability than doing nothing. However, the best practice would be to replace the inspection activities with continuous monitoring. For simplification, and without loss of utility, detectability at any location is viewed as the most desirable rating of 1 if a monitor is installed in that location, and 10 if not. An output of the process proposed herein is a list of locations to actively manage, all of which will have a monitor installed. Therefore, all would receive the same detectability rating of 1. Multiplying every occurrence rating and severity rating by 1 adds no value, $O*S*1 = O*S$. For these reasons, detectability is ignored in RPN calculations for this research.

4.1.3.4 Calibration of RPN to the operator's risk preferences

An often-cited complaint of the base FMEA model is the assumption that a given RPN may represent a high probability of a low consequence event or the same RPN may represent a low probability of a very high consequence event. These may not be equivalent in the decision makers viewpoint depending on their risk tolerance. For instance, conservative decision makers will be sensitive to very low probabilities of severe failure. Hence, a calibration step to align the RPN with the operator's utility function is proposed.

The matrix below (figure 4-12) demonstrates the relationship of occurrence scores and severity scores in which severity scores across the horizontal axis are associated with qualitative labels of the potential consequences. In this example, the decision makers have come to consensus that the worst consequence of a failed pipe is the possibility of public health to be compromised through water contact which may spread over large areas. In addition, occurrence scores are depicted on the vertical axis. Under stock FMEA the occurrence score might be strictly associated with the failure likelihood as a score of 1 is associated with 10% likelihood of failure, 2 is associated with 20% likelihood…etc.

The proposed calibration step is performed by modifying occurrence scores to the likelihood probabilities so that the decision makers are indifferent amongst RPN's of identical value. This is done by iterative questioning. For example, consider the case in the matrix below (figure 4-12) of an occurrence score of 10 and a Severity score of 5 that produces an RPN of 50, at the same time, an occurrence score of 5 combined with a Severity score of 10 also produces an RPN of 50. Therefore, the decision makers have agreed that a 40% likelihood of “aquatic life support comprised – minor” is an equally acceptable risk to a 10% likelihood of “public health compromised through water contact”. If decision makers do not agree with this equivalence, then the failure likelihood is re-mapped to occurrence scores until an agreement can be reached.

Occurrence Score	Indicative Failure Liklihood										
10	40%	10	20	30	40	50	60	70	80	90	100
9	30%	9	18	27	36	45	54	63	72	81	90
8	25%	8	16	24	32	40	48	56	64	72	80
7	20%	7	14	21	28	35	42	49	56	63	70
6	15%	6	12	18	24	30	36	42	48	54	60
5	10%	5	10	15	20	25	30	35	40	45	50
4	5%	4	8	12	16	20	24	28	32	36	40
3	3%	3	6	9	12	15	18	21	24	27	30
2	2%	2	4	6	8	10	12	14	16	18	20
1	1%	1	2	3	4	5	6	7	8	9	10
	Severity Score->	1	2	3	4	5	6	7	8	9	10
	Indicative Potential Consequences	Overflow unlikely to be noticed or to cause ecological damage	Loss of enjoyment due to odor or visible sewage – low population density	Loss of enjoyment due to odor or visible sewage – high population density	Traffic disruption	Aquatic life support compromised - minor	Aquatic life support compromised - major	Public health compromised through drinking water or consumable fish supplies	Public health compromised through surface contact - suburban	Public health compromised through surface contact - urban	Public health compromised through water contact

Figure 4-12: A matrix of the relationship between occurrence scores and severity scores

4.2 Defining the objective

There were two competing alternatives considered for the objective function of the FMEA.

1. Maximize the sum of RPNs such that the highest risks across the piping network are identified and actively managed. The advantage of this objective is that it directs resources towards those risks that are most likely and most severe. In the matrix above, this would lead a search towards locations with a 40% or higher chance of compromising public health through water contact.

2. Identify, as efficiently as possible, a manageable set of locations that are classified as unacceptable risk. Given the resource constraints of continually searching for risks across space and time, this objective was adopted for this research. Furthermore, the concept of risk threshold is applied, separating acceptable risks from the unacceptable ones which must be actively managed.

The rationale for this choice is that the iterative nature of the discovery of risk priorities precludes objectives that require a risk assessment of all locations. In an ideal but impractical world, every manhole in a collection system would be continuously monitored. Risk management would then be a matter of choosing the highest RPN's and taking action to lower the risk likelihood and/or consequences in the order of the RPN values.

Practical resource limitations allow only a relatively small number of locations to be monitored and, in order to get a wider perspective of system's risk, these monitors must be periodically moved. Therefore, an objective of this research is to provide decision support tools for the number of monitors and their movement paradigm.

The responsibility of wastewater utility operators motivates them to take action on high-risk situations as soon as possible. It is not acceptable to defer intervention until a possibly lengthy risk assessment process is completed. For example, using the matrix above, consider during the course of assessing locations for risk, a location is determined to have a 25% chance of failure (O=8) that could lead to compromising consumable fishing waters (S=7) for an RPN of 56. If the decision makers have determined that this risk to be unacceptable they will be compelled by legal, ethical, and possibly political motivations to actively manage that location even though higher risks may be discovered in the future through additional searching.

Funding is a constraint beyond the risk assessment phase. Funding limits the number of risky locations that can be actively managed. Therefore, it does little good to locate manholes that have a high risk which cannot be mitigated due to funding. On the other hand, it is of little value to have available budget to manage risk with insufficient budget to locate those risks in the assessment activity. Hence, in the context of this research study, the funding available to actively manage risk is assumed to be fixed. Therefore, it is a constraint of the objective function. At the same time, funding available to conduct the risk assessment is assumed to be variable with a goal of minimization. Thus, a worthy goal is to locate as many sites to actively manage as the budget will allow, which will result in a maximum risk reduction.

This objective of minimizing the cost of finding a number of manholes exceeding a threshold RPN is a combinatorial optimization problem that may be formulated as such:

$$\text{Minimize cost} = \text{Min} \sum i * a * c \tag{4-5}$$

$$\text{S.T. } |\{r \in R | r >= R^T\}| >= n$$

Where,
"i" is the number of iterations before a stopping criteria is reached
"a" is the number of agents parameter
"c" is the cost per agent per iteration parameter
"r" is the RPN of an individual location
"R" is the set of all RPNs discovered
"R^T" is the threshold RPN specified as a parameter
"n" is the number of locations that can be actively managed as a parameter.

The solution set of this constrained optimization is the combination of locations that should be actively managed for risk reduction at a given time. This is set as a minimum so that at least the desired number of locations is discovered in the optimization. Due to the fact that sewers are dynamic, and presumably the risk mitigating actions will change the RPN of actively managed sites, the set of locations satisfying the constraint will continuously change over time.

It is recognized that setting the objective function as binary, e.g. a site is either acceptable risk or unacceptable risk, allows the possibility of higher risks going undiscovered. For instance, should a system operator stop at finding a set of sites that overflow in the streets recognizing that the possibility that some undiscovered failures may overflow on the beach and cause greater impact? The proposed framework in this research study can accommodate this dilemma through setting a very high RPN as a risk threshold. Decision makers may also segment the objective by allocating fixed resources towards finding locations of moderate to high risk and another set of fixed resources to the most severe risks.

Additionally, consideration was given in this research study to a multi-objective problem formulation with a goal of minimizing cost and risk simultaneously. The problem formulation chosen takes into consideration many factors. The qualitative consequence rating in FMEA takes into account the social and environmental dimensions of the problem while financial considerations are incorporated in the objective function. Thus, all components of the “triple bottom line” are considered (Slaper and Hall 2011). The final reason for a single objective formulation is that if offers a less complex framework for risk management to an industry that values simplicity, based on interviews conducted during this study.

4.3 Understanding the distribution of risk across a sewer network

No prior research has attempted to quantify the specific distribution of RPNs across sewer systems. In this research, the focus is very specific in that it attempts to understand the distribution of risk consequences and risk probabilities due to limited capacity. To have a complete knowledge of the distributions of this risk would require continuous monitoring everywhere all of the time. This is not currently practical. Therefore, the methodology employed in this research analyzed available data on reported overflows in a medium sized sewer system in the United States. The development of a hypothetical distribution of RPN’s is based upon the drivers of blockage formation found in prior research. These two sources served as inputs to arrive at what is proposed to be a realistic distribution of risk. Recognizing the system-to-system variation of risk distribution, it was important to allow this distribution to be modified within the simulation to test the robustness of the search techniques.

4.3.1 Prior research

The majority of the prior research related to the distribution of risk geographically across a sewer network is concerned with establishing statistical models to predict failure. Environmental factors as well as pipe characteristics have been used as predictors to construct such models. Thus, understanding the geographic distribution of these risk predictors provides potentially quantifiable insight into the geographic distribution of risks.

Table (4-6) below summarizes the most cited predictors for failures due to blockage in sewer pipes:

Table 4-6: Most cited predictors for failures due to blockage in sewer pipes

Predictor Class	Predictor	Authors
Pipe design attributes	Combined versus separate sewers	(Baur and Herz 2002) (Ugarelli et al. 2010)
	Pipe Diameter	(Baur and Herz 2002) (Marlow et al. 2011) (Ugarelli et al. 2010)
	Manholes/inspection chambers	(Hafskjold et al. 2018) Lilywhite et al. 1978 in (Hillas 2014)
	Pipe depth from surface	Davidson and Orman 1999 in (Marlow et al. 2011) (Pohls, Bailey, and May 2004)
	Pipe material/joint type	(Baur and Herz 2002) Littlewood 2000 in (Marlow et al. 2011) (Marlow et al. 2011)
	Pipe slope	(Arthur, Crow, and Pedezert 2008) (Hafskjold et al. 2018) (Ugarelli et al. 2010)
Pipe aging attributes	Construction period	(Baur and Herz 2002) (Hafskjold et al. 2002)
	Pipe Age	(Jin, Mukherjee, and Asce 2017) (Pohls, Bailey, and May 2004) (Ugarelli et al. 2010)
	Structural condition	Blanksby et al. 2003 in (Hillas 2014) Roberts et al. 2006 in (Marlow et al. 2011) (Savić et al. 2006)
Environment	Presence of trees/roots	Roberts et al. 2006 in (Marlow et al. 2011) (US EPA 2009) (WSSA 2013)
	Prevalence of food preparation establishments	(Chu and Hsu 1999) (Husain et al. 2014)

Predictor Class	Predictor	Authors
	Soil characteristics	Enfinger 2009 in (Hillas 2014) (Jin and Mukherjee 2010) (Marlow et al. 2011)
Other	Number of past failures	(Fenner and Sweeting 1999) (Hafskjold et al. 2018)

A question examined in this research is whether or not the distribution of the predictors of pipe blockages shown in table 4-6 will reveal the distribution of blockages. Two of the researchers shed doubt on this question. Marlow et al. (2011) concluded that "with the available data, it was difficult to show definite causal relationships between the various factors considered in the analysis. Furthermore it was clear that a single factor could not explain the differences in blockage rate observed even within a single company" (Marlow et al. 2011). Moreover, Hafskjold et al. (2018) reported that "for 75% of blockages in a study, a clear cause could not be identified and that only 20% of blockages could be attributed to a sewer defect" (Hafskjold et al. 2018). In contrast to predictive modeling, the search methods examined in this research reveal the distribution of risk empirically, through the efficient collection of performance data.

To validate the methodology of this study it was only important to show how the pipe failures are clustered. It was reasoned that if the causal factors behind blockage formation appeared in geographic clusters, then blockage formation should also appear clustered. An obvious example of this reasoning is root formation. In the absence of vegetation there cannot be blockage caused by roots, so if it could be shown that vegetation is clustered over the area of a sewer system, then blockage caused by roots should also be clustered.

4.3.2 Measures of spatial autocorrelation

For the purposes of validating a simulation of risk across a sewer network, it was necessary to select measures of spatial autocorrelation and a particular method to reasonably approximate the frequency distribution of RPNs. These measures were used in the calibration of the simulation, and also provided parameters to modify the distribution of risks in the simulation to test the robustness of the search algorithms employed.

The Moran's I index was selected as the measure for spatial autocorrelation between features (Zhang et al. 2008). The output of the Moran's I index includes both a z-score and p-value to indicate the significance of clustering. The index value is given as (ESRI 2018):

$$I = \frac{n}{S_0}\frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{i,j} z_i z_j}{\sum_{i=1}^{n} z_i^2} \tag{4-6}$$

where z_i is the deviation of an attribute for feature *I* from its mean $(x_i - \bar{X})$, $w_{i,j}$ is the spatial weight between feature *I* and *j*, *n* is equal to the total number of features, and S_0 is the aggregate of all the spatial weights given by:

$$S_0 = \sum_{i=1}^{n}\sum_{j=1}^{n} w_{i,j} \tag{4-6}$$

The z_I-score for the statistic is computed as:

$$Z_I = \frac{I - E[I]}{\sqrt{V[I]}} \tag{4-7}$$

where:

$$E[I] = \frac{-1}{(n-1)}$$
$$V[I] = E[I^2] - E[I]^2$$

In the case of reported overflow data, the data needed to be aggregated before Moran's I index could be calculated. Moran's I index requires that the attribute of interest contain a variety of values rather than a binary indicator of whether or not an event, such as an overflow at a particular manhole, occurred.

Aggregation was performed by overlaying a grid on the map of the sewer pipe network. Grid cells were removed if there were no pipes within the extent of the cell. Then, for each cell, the number of locations (manholes) and reported overflows was counted. The density of overflow count to manhole count is depicted in the map below (figure 4-13). Each dot represents a reported overflow while the color of the grid cells represents the overflow densities. Using overflow densities per cell, the Moran's I index could be calculated and the spatial autocorrelation could be tested. Areas with high failure density are commonly referred to as “hot spots” in the wastewater industry.

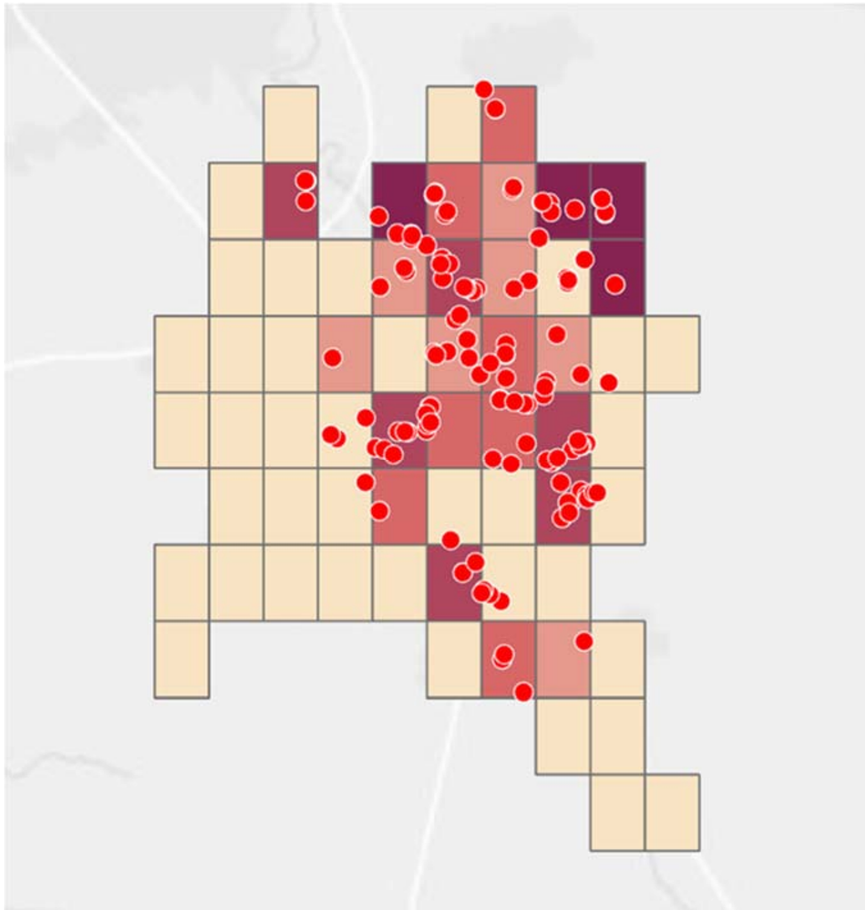


Figure 4-13: A map of the density of overflow count to manhole count

A potential problem that could arise is that the sewer network is, by default, spatially autocorrelated across geographic boundaries like city limits. Hence, Moran's I index could indicate clustering by the simple fact that sewer pipes are connected to each other in close proximity. In order to overcome this problem, two steps were taken. The first was the elimination of any grid cells that did not contain sewer pipes so that the analysis was restricted to land area containing the sewer network. The second was the use of overflow proportions rather than overflow counts. This normalized the spatial failure data to account for different grid cells containing different manhole counts.

4.3.3 Characteristics of reported overflows

Defining failure as a surcharged pipe created difficulties in terms of corroborating historical data. Pipe surcharges most probably go undetected in the absence of a flow monitor, timely visual inspection of the pipe, or if the sewage is not observed nor reported by humans.

Previous studies of complaint databases provide insight into the latter category. Rodriguez (2012) studied complaint data from customers who noticed a failure in the sewer system in Bogota, Columbia. One conclusion from that study was that the data implied that blockages come in clusters. A visual observation of the maps published by Rodriguez supports the clustering of blockage complaints for pipes. The study went further to show associations between pipe physical properties and blockage complaint density.

One method employed in this study was to collect observed overflow data which is more readily available than surcharge or blockage data. Analyzing the spatial autocorrelation and frequency distribution of the overflow data was assumed to provide a reasonable approximation of the spatial autocorrelation and frequency distribution of surcharge occurrence probabilities.

The most comprehensive data used in this research were from a sanitary sewer network consisting of 14,600 manholes, referred to here as “City A”. The systems operator provided GIS data and reported overflow data from January 2004 through April 2017. There were 250 reported overflows during this period. The overflow data was cross-referenced by manhole identification numbers in order to geocode the overflow locations in the manhole layer of the GIS database. In the below figure (4-14), the yellow circles indicate the reported overflow locations and the larger circles indicate areas of repeated overflows. However, the yellow dots alone represent incident data that is not useable for calculating the Moran's I statistic. This was resolved using the fishnet grid procedure described in the previous section. The white lines depict the sewer pipes that are covering the full extent of the collection system.

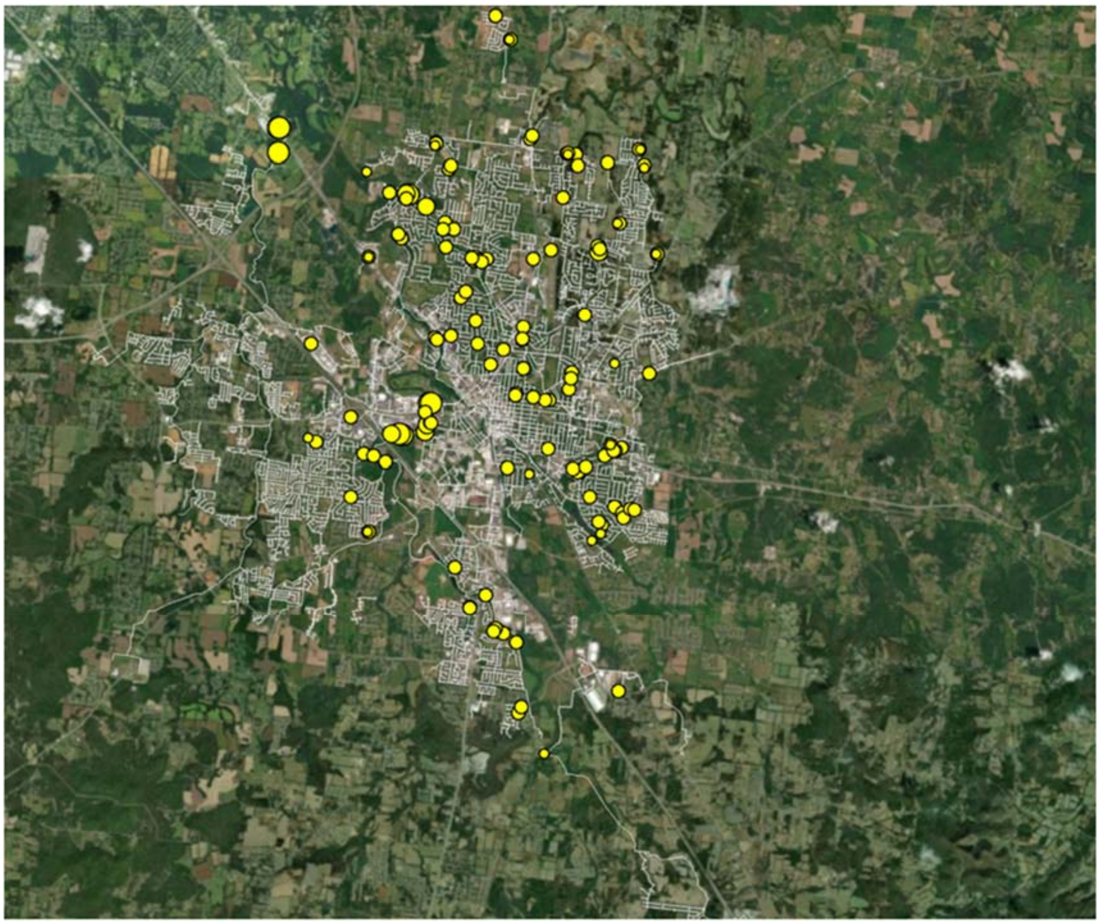


Figure 4-14: City A sewer overflow data

In addition, further analysis was conducted on other collection systems where limited data was available. For example, overflow data was publicly available for the City of Sacramento, CA, however detailed GIS data was not available to calculate overflow proportions. Therefore, the spatial autocorrelation analysis was conducted based on the overflow density within each geographic cell without normalizing for manhole density. Another example is the city of St. Louis, MO. Data was also available for this city. However, the system is designed with constructed overflow locations that are intentionally clustered. Data was visually examined for cases of published reported overflows, including the State of California, Boston, Columbus, Mobile, Hampton, Baltimore, San Francisco, and Louisville. Based on this examination, it was found that the data from other collection systems was consistent in terms of clustering with the findings of the collection system used to calibrate the simulation.

4.3.4 Characteristics of hypothetical distribution of RPN

A second method employed to estimate the failure distributions was by preparing an estimate of hypothetical RPN's based on the risk factors identified in prior research. Specifically speaking, the available relevant data from City A used in the estimation of the hypothetical RPNs were:

1. Pipe diameter
2. Pipe material
3. Pipe age
4. Pipe grade
5. Land use as indicated by city zoning maps
6. Vegetation coverage as measured by the Normalized Difference Vegetation Index (NDVI)
7. Restaurant density
8. Failure consequence ratings

After identifying the risk factors, the following steps were conducted to create the hypothesized RPNs.

4.3.4.1 Extract risk factor values

The first step in this process was to extract the values of these risk factors from their relevant data sources as shown in table (4-7). Each pipe segment in the sewer system was assigned a value for each of the risk factors according to the data sources shown in the table below. Therefore, there was significantly more data than in the case of reported overflows which allowed for a denser fishnet grid of 20x20 rather than the 10x10 used for reported overflow data.

Table 4-7: Risk factors and their respective data sources

Risk Factor	**Source of Data**
Pipe Diameter	City A’s GIS pipe layer
Pipe Material	City A’s GIS pipe layer
Pipe Age	City A’s GIS pipe layer
Pipe Grade	City A’s GIS pipe layer
Land Use	City A’s GIS zoning maps
Vegetation Coverage	NDVI publicly available data
Restaurant Density	Restaurant locations from Google Maps
Failure Consequence Rating	Manual analysis of City A’s pipe layer using severity scoring rubric

For each of these risk factors, the Moran’s I statistic was calculated to determine to what degree the factor appeared to be clustered. The rationale behind the degree of clustering is that if the drivers of risk are clustered then it is more likely that the symptoms of risk would also be clustered. In addition, the procedure of overlaying grids and computing Moran’s I for each risk factor was also utilized in this analysis.

4.3.4.2 Standardize the values of each risk predictor

The next step in creating the hypothesized RPNs was to standardize the values of each risk predictor. This standardization step was conducted by using the Min-Max scaling through a linear transformation function from 0-10 (equation 4-7). However, in cases where higher values indicated lower risk, the standardized values were inverted which created some degree on non-linearity in the transformed values.

$$X_{sc} = \frac{X - X_{min}}{X_{max} - X_{min}} \,.\, 10 \qquad (4\text{-}8)$$

Due to the different nature of the values of the risk factors and their impacts on the overflow risk, each of these risk factors had to be standardized through a tailored process.

Regarding the pipe diameter, according to Marlow et al. (2011), the smaller the diameter of the pipe, the higher the risk of overflow. Thus, the inverted standardization code was used, and the resulting values were not linear to the pipe sizes as shown in figure (4-15):

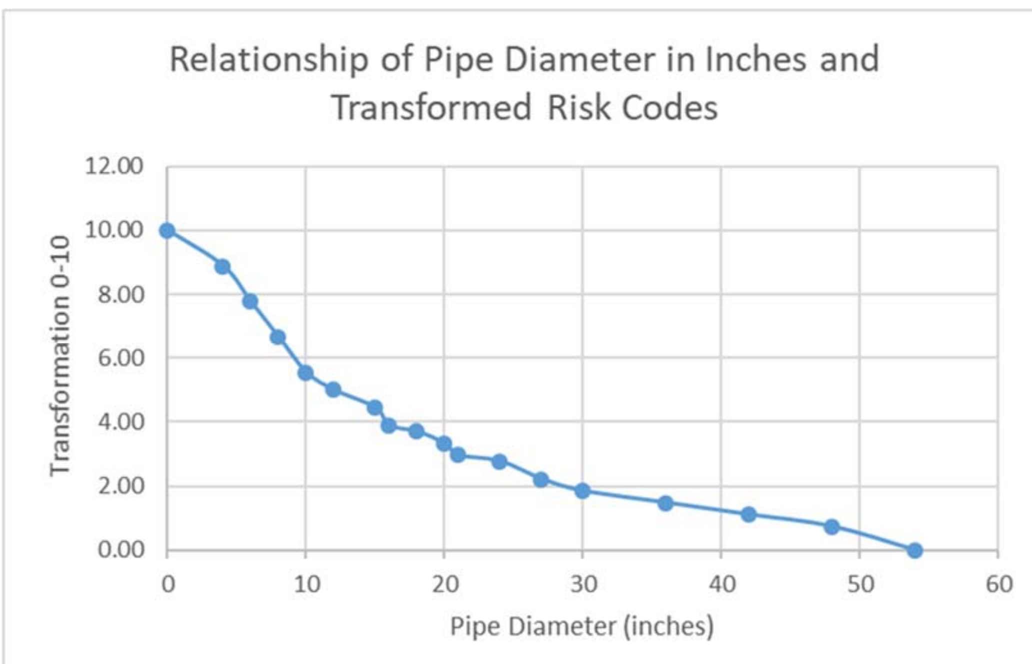


Figure 4-15: Relationship between the pipe diameter and the risk codes

Risk rating of the different pipe materials was based on the study conducted by Ugarelli in 2010 and as shown in table (4-8):

Table 4-8: Risk rating of different pipe materials

Risk Category	Material	Risk Rating
Low Risk	Cast Iron Ductile Iron HDPE Reinforced Concrete SPL Verified Clay	0.00
Moderate Risk	Hobas Cured in-place lining	6.50 7.00
High Risk	PVC	10.00

At the same time, the standardization of the pipe age factor was a straightforward linear transformation as the risk increase with the pipe age (grouped every 10 years) and is evident in table (4-9):

Table 4-9: Risk rating of the pipe age

Age (years)	Agecode	Frequency
0	0.00	902
10	1.11	4,959
20	2.22	3,581
30	3.33	1,878
40	4.44	1,281
50	5.56	775
60	6.67	331
70	7.78	692
90	10.00	204

Similar to the pipe diameter, the inverted code was used to standardize the values of the pipe grade as higher grades produce higher liquid velocity which self-cleans the pipe by forcing the debris, roots, and grease down the pipe, hence reducing the risk of blockage. This non-linear relationship is depicted in figure (4-16):

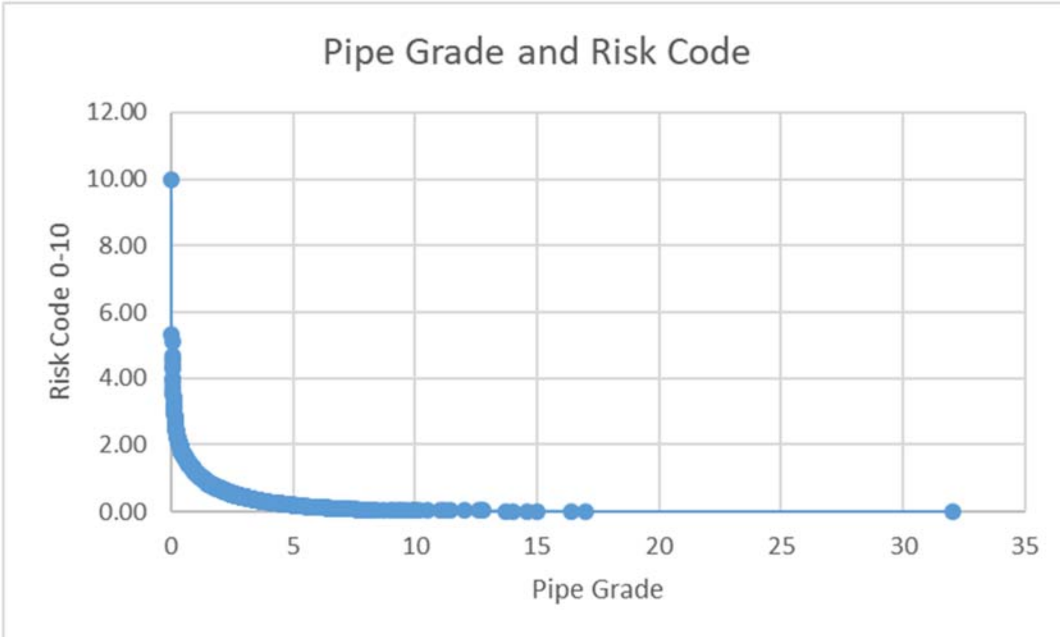


Figure 4-16: Relationship between the pipe grade and the risk codes

Regarding the relationship between the land use and the blockage risk factor, the following table (table 4-10) shows the assumed relationship based on the city's zoning code.

Table 4-10: Risk rating of the different land uses

Land Use	Basis of Estimate	Risk Rating
Residential	High density of service connections. Food prepared in homes. Flushable wipes disposed in homes	10
University	Moderate service connection density, food preparation, and flushables.	8
Commercial & Parks	Low density of service connections. Public restrooms.	6
Industrial	Low density of connections. Expected low food prep. Possible chemical disposal.	4
Other		2

Perhaps the most complex standardization process of all was the one conducted for the vegetation. This process started by extracting the vegetation indices, which are indicators that describe the greenness, the relative density and health of vegetation, for each pixel in a satellite image from the USGS database. Then, the NDVI values were generated from USGS raw landsat bands from May 2017 in 30m resolution using ArcGIS. After generating the NDVI values, they were standardized to a range of 0-1 and then assigned to the nearest tenth interval. Finally, they were standardized to a range of 0-10, in which higher numbers represent more dense vegetation, consequently with a higher risk of blockage due to root intrusion. This is presented in table (4-11).

Table 4-11: Risk rating of the land vegetation

NDVI Group	NDVIcode	Frequency
0	0.00	14
0.1	1.67	1,219
0.2	3.33	3,335
0.3	5.00	6,796
0.4	6.67	2,911
0.5	8.33	336
0.6	10.00	7

Regarding the restaurant density, a restaurant count was assigned to the manholes based on the number of restaurants within 1,000 ft. The standardization process was a linear one based on the restaurant count as the size of the restaurant was not taken into consideration in this study. Table (4-12) shows the different risk ratings for the different restaurant numbers.

Table 4-12: Risk rating of the restaurant density

Restaurant Count	Restcode	Frequency
0	0	10,872
1	0.4	965
2	0.8	617
3	1.2	502
4	1.6	288
5	2.0	337
6	2.4	220
7	2.8	134
8	3.2	145
9	3.6	111
10	4.0	74
11	4.4	68
12	4.8	54

Restaurant Count	Restcode	Frequency
13	5.2	52
14	5.6	49
15	6.0	16
16	6.4	21
17	6.8	28
18	7.2	37
19	7.6	13
20	8.0	2
21	8.4	3
22	8.8	4
23	9.2	1
25	10.0	4

4.3.4.3 Synthesizing risk probabilities

After standardizing the values of the different risk factors, the risk probabilities of these factors were synthesized through the following multi-step process:

1. Calculate a root blockage risk index as the NDVI risk score as it is the only data available directly that is related to root intrusion.
2. Calculate a grease blockage index as the average of restaurant density score and the city zoning score as the amount of grease in the pipes mainly comes from both restaurants and households.
3. Calculate a silt blockage index as the pipe material risk score as silt occurs due to pipe deterioration and structural failure which can be predicted through the pipe material.
4. Calculate a global blockage index as the average of pipe diameter risk score, age risk score, and pipe grade risk score because these factors influence blockage risk from roots, grease, and silt.
5. Calculate the average of the above four indexes to reach an overall blockage probability index.

4.3.4.4 Calculating risk priority numbers

The final step to reach the hypothesized RPNs is to calculate the risk propriety numbers as the product of the risk occurrence ratings and risk consequence ratings were the hypothetical risk priority numbers used as an input to the simulation. The resulting distribution of the RPNs is shown in figure (4-17).

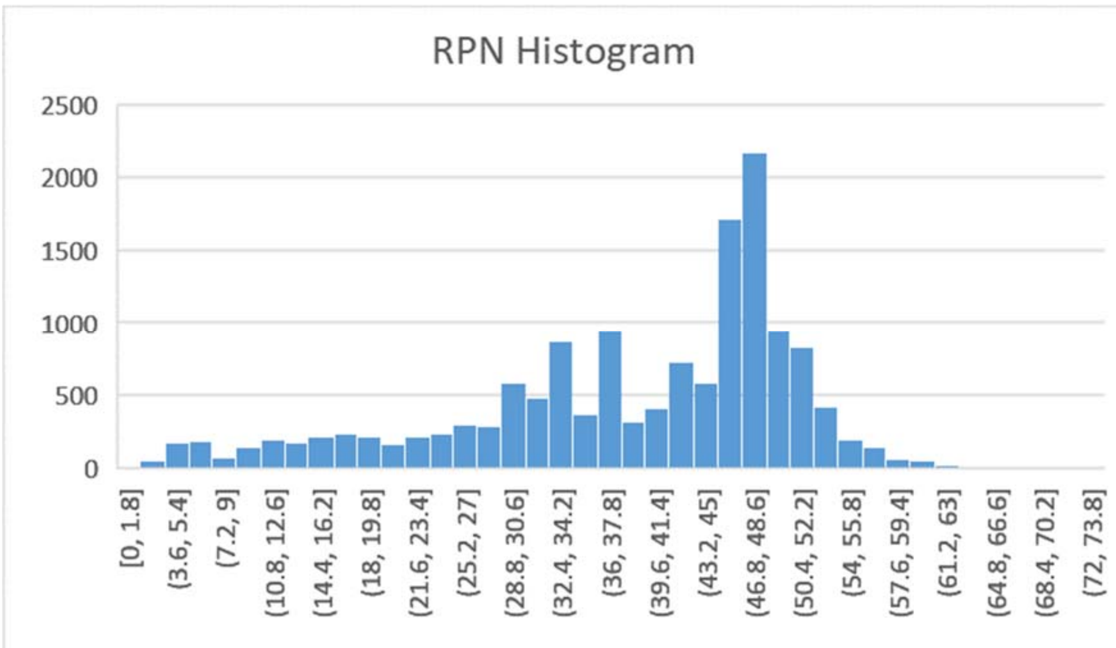


Figure 4-17: Distribution of the resulting RPNs.

4.4 Evaluation of search algorithms

4.4.1 Identify a set of candidate algorithms

As argued previously, the class of algorithms that fit this structure are metaheuristic search techniques that solve combinatorial optimization problems in a single solution evolution, also referred to as trajectory methods. Five of the most-widely used of these algorithms are Simulated Annealing, Tabu Search, Greedy Randomized

Adaptive Search Procedure (GRASP), Variable Neighborhood Search, and Local Search – Basic, Iterated, and Guided.

In this research study, simulated annealing was selected as the most-suitable algorithm for the search technique problem defined above. All the above algorithms share some common characteristics. They all provide approximate solutions and do not guarantee a global optimum. Furthermore, in very large combinatorial optimization problems like the one studied in this research, it would be very rare that the algorithm would find the global optima. Because the global optimum does not serve as a stopping condition, each algorithm has its own stopping condition based on some condition, typically related to controlling the cost of searching. Also common is that they will occasionally accept moves to inferior solutions which serves the vital purpose of allowing the search to escape local optimum solutions, particularly in early iterations. These methods are adaptable to a wide range of problems, requiring only:

1. A representation of the solution space
2. A method to calculate the objective function at each iteration
3. A neighborhood function
4. A method to select moves within the neighborhood

Simulated annealing has some unique features that will be presented in detail below.

4.4.2 A description of simulated annealing

Simulated annealing derives its name from the analogy to the physical annealing process of cooling metals. In order for metals to cool without defects in their structure, the temperature and cooling rate must be carefully controlled. Likewise, in simulated annealing, a cooling rate is employed to allow convergence to optimality while avoiding local optima. It has a distinct advantage of converging to a global optimum, given sufficient randomness and very slow cooling. A flowchart of the base simulated annealing algorithm (BSA) is shown in figure (4-18).

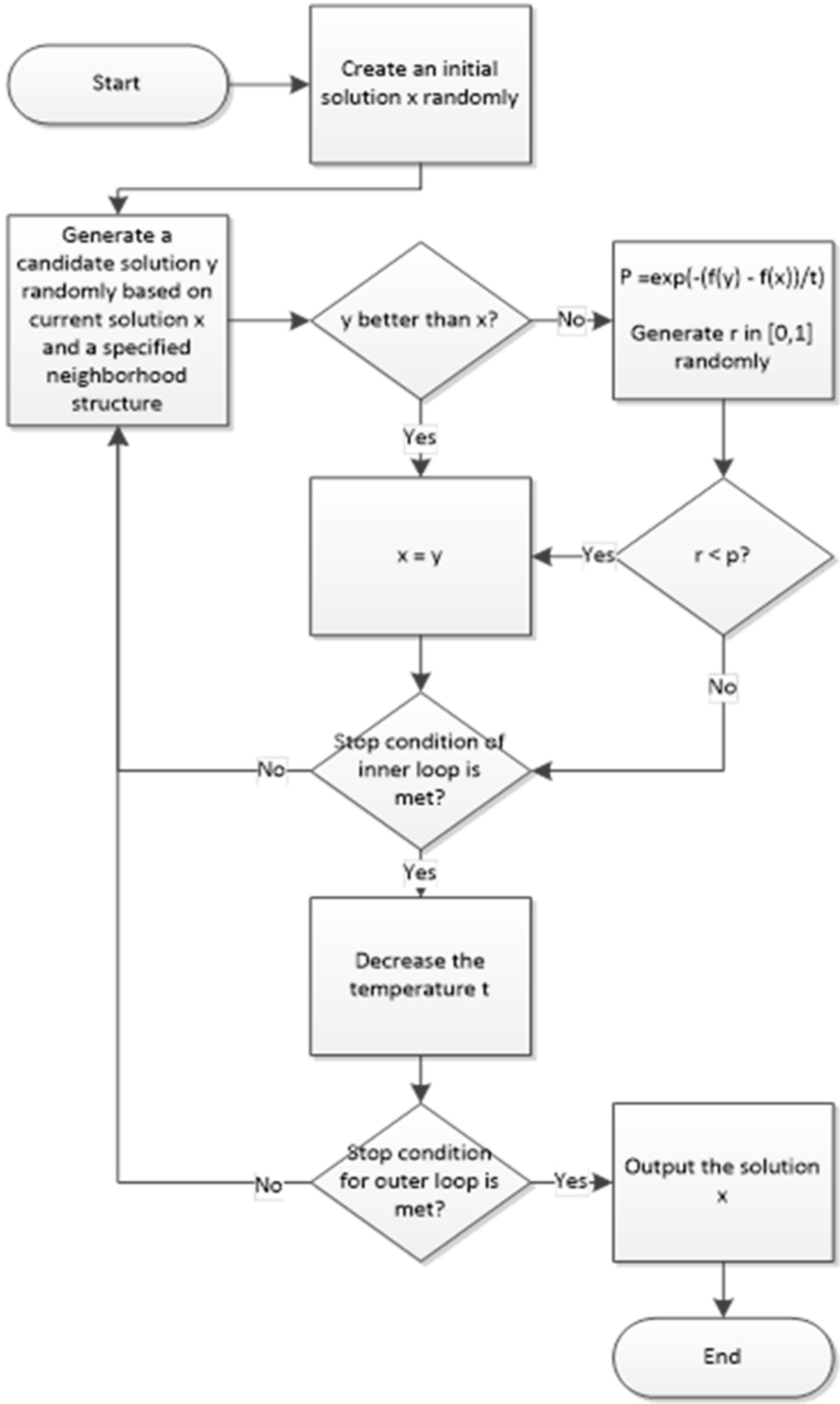


Figure 4-18: Flowchart of simulated annealing algorithm (Zhan et al. 2016)

Simulated annealing employs a unique inferior move mechanism which means that if a candidate solution is superior to the current solution, the move to a better solution is always allowed. However, if a candidate solution is inferior to the current solution, the move may be allowed probabilistically, depending on the temperature and the degree of inferiority of the candidate solution. This is called the transition probability. The transition probability is based upon the Boltzmann factor, which is the ratio of the Boltzmann distribution at two energy states.

$$\frac{F(state2)}{F(state1)} = e^{\frac{-(E_1 - E_2)}{T}} \tag{4-9}$$

where E_1 and E_2 are the fitness function values of the current solution and candidate solution, respectively, and T is the current temperature variable in the range 0-100.

Since the constraint in this study is a requirement for high fitness values, an inferior move is considered one where the candidate solution has a lower fitness value than the current solution.

At each test of accepting an inferior move, a random number between 0 and 1 is compared to the transition probability. If the random number is less than the transition probability, the inferior move is made. In this research, the “energy states” are represented by RPN values.

Consequently, when evaluating a potential move, the difference in RPN values and the current temperature determine the probability of accepting inferior moves. In figure (4-19), the x-axis is the absolute value of the difference between two RPNs (RPNDelta) and the y-axis is the temperature on a scale of 0-100. The shading represents ranges of inferior move acceptance probabilities (AcceptProb). This figure illustrates that significantly inferior changes have a very low probability of acceptance at all temperatures. For example, a RPN Delta > 30 would be accepted less than 5% of the time even at the highest temperatures. The graph also illustrates that even small inferior moves have probabilities that drop off significantly as the temperature cools. For example, a change as small as 5 in RPN value has only a 37% chance of being accepted once the temperature has cooled to 50. Therefore, the greatest freedom of moves is achieved in early iterations by setting a slow cooling rate. In other words, the algorithm becomes greedier as the temperature parameter declines in later iterations.

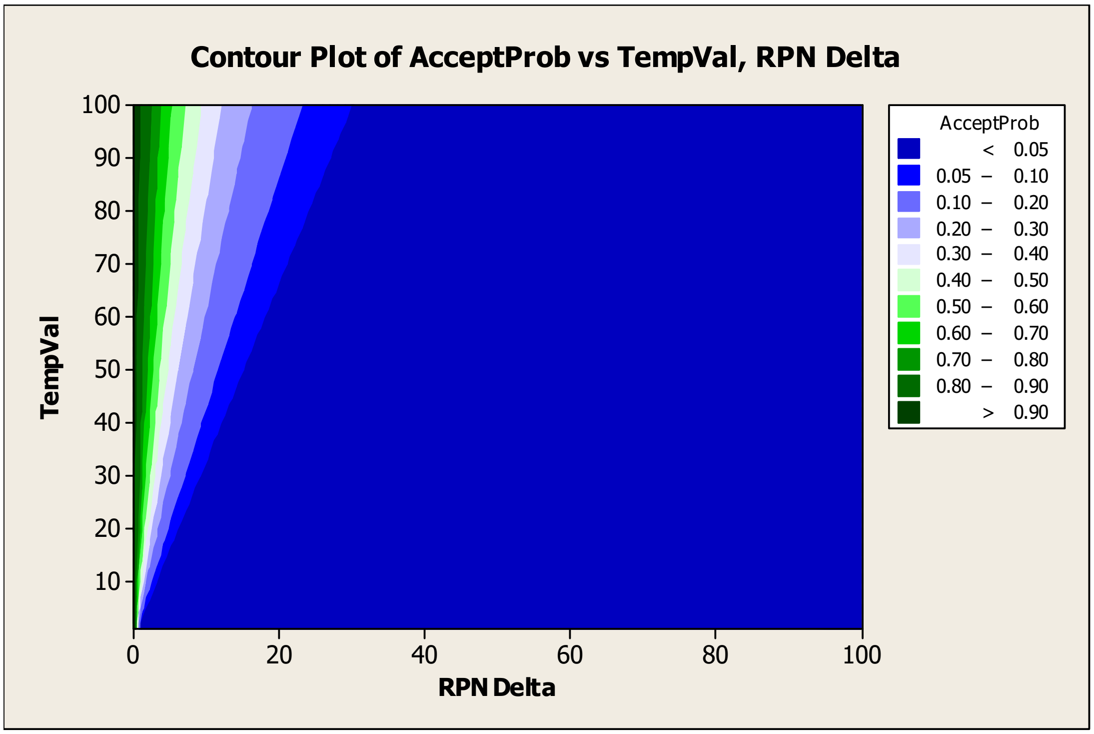


Figure 4-19: Conditions and probabilities of accepting inferior moves.

The temperature in the simulated annealing is a parameter that starts at its highest value and is reduced at each iteration. This reduction is a parameter known as the “cooling rate”. There are several commonly used techniques to control cooling. Yang (2010) identified linear cooling and geometric cooling as two commonly used annealing schedules. In a linear cooling schedule, the temperature is reduced by a constant at each iteration, while in a geometric cooling schedule the temperature is reduced by a factor at each iteration.

$$T(t) = T_0\alpha^t, \ t = 1, 2, \ldots, t_f \quad (4\text{-}10)$$

where, T is the temperature parameter, t is the iteration index, and alpha is the cooling rate.

In the simulation used in this research, a geometric cooling schedule was employed. A practical reason for this was to ensure that the temperature never went below zero. Thus, at each new iteration of the search, t, the temperature, T, was modified as:

$$T(t) = T_{t-1}(1 - \frac{\alpha}{100}) \quad (4\text{-}11)$$

$$where\ 0 < \alpha < 100$$

This new formula recognizes the fact that the cooling rate was expressed as Yang's (1 – α) as one of the objectives of the research is to determine what affect, if any, cooling rates had on the efficiency of the search.

The last main characteristic of the simulated annealing that was beneficial in this research is the neighborhood function. In simulated annealing, the algorithm can be viewed as progressing sequentially through a series of states by some probabilistic mechanism. From any given state there are a limited number of states that can be transitioned to. These allowed states are called "neighbors". Consequently, the performance of the simulated annealing algorithm is highly dependent on the neighborhood structure chosen (Goldstein and Waterman 1988).

4.5 Selection of simulation technique

4.5.1 Accommodation of the research objectives

No tools were found in this research to adequately evaluate the performance of various search algorithms on the problem structure under study. Therefore, the research required the construction of a specialized simulation to aid in the selection of the search algorithms and its suitable parameters.

The principle need for simulation in this research is to evaluate particular combinatorial optimization algorithms with varying parameters in respect to the objective function and the constraints previously stated. Central to this was to evaluate a base simulated annealing algorithm and research methods to improve its performance, termed the enhanced simulated annealing algorithm (ESA).

There were several requirements for the simulation method to be used in this research:

1. The simulation method was required to accommodate a wide range of monitoring locations and available flow monitors which, in the case of sewer networks, leads to a very large solution space.
2. The simulation method was required to accommodate simulation across a geospatial network. Unlike some other sensor placement problems where sensors may be placed at any point in space or on a uniform grid, the problem under consideration in this research only allows sensor placement at discrete locations as defined by the map of the sewer network.
3. The simulation method was required to accommodate varying degrees of spatial autocorrelation in risk since the probability of failure at any particular location is dependent upon the risk of the surrounding locations.
4. The simulation method was required to have the capability of ranking the efficiency of various optimization algorithms. Since the cost of evaluating any particular solution is high, the best algorithms are those that converge quickly

on a “good” solution that is unlikely to be the global optimum but is good enough to reveal valuable information to justify continuing the search towards even better combinations.

5. The simulation method was required to accommodate trajectory methods of metaheuristic search. This required a great deal of flexibility to be designed into the simulation, such as the ability to write custom software to direct the movement of agents.

4.5.2 Accommodation of the problem structure in simulations

In order to be able to determine the suitability of agent-based models (ABM) to the requirements imposed by the objective function in this research and its associated constraint, each of these requirements was assessed against the different ABM capabilities as outlined in the following sections.

4.5.2.1 Agents and environment as representations of monitors and manholes

The ABM components can be directly associated to the structure of the sensor placement problem described in the previous sections. Specifically speaking, flow monitors can be readily represented by agents that move within an environment, while the environment represents the geospatial world of the sewer network. In model terms the problem represents movement of agents (flow monitors) through an environment (discrete locations in a network) that is projected in Euclidian space. These agents move in a distance and direction that is controlled by a search algorithm and its parameters. Moreover, agents learn from their experience by storing, as attributes, the risk characteristics of the candidate monitor locations that they visit. The agents feed the information that they acquire along their journey back to the search algorithm, which directs future agent movements presumably towards locations of highest risk of failure. Consequently, manholes and pipes may be placed in a network topography in the simulation based on empirical data from GIS systems. Simulation applications such as Netlogo and AnyLogic directly import GIS data to project a very accurate representation of the sewer network.

4.5.2.2 Modeling the propagation of risk

A critical attribute of the simulated environment is that it must contain a realistic distribution of risk in space. Wegener (2000) observed that the geospatial models depend on the location of the phenomena being modelled to the extent that if one or more locations changed, the results of the model would change. This suggests that risk should be assigned at the manhole level since the results of the model will be the assignment of monitors to manholes.

An RPN ranging from 0-100 was used as the state variable for the risk, with 0 indicating a near impossible probability of pipe failure with no consequences and 100 representing an almost certain probability of failure with the highest consequences. The goal was for the monitors to seek “hot spots” in the environment where the RPN is highest, as RPNs are expected to cluster within the environment as explained previously.

Due to the uncertain nature of the distribution of risk associated with sewage pipe failure, a way to deal with this uncertainty is to employ a simulation method that was robust to a wide range of realistic risk scenarios. As Batty (2012) noted, ABM became very popular in the past two decades as its modeling style has the capability of reflecting the richness of our world. This was an additional motivation for the use of

ABM in this research. Based on the analysis of hypothetical risk as a function of risk predictors and upon the analysis of reported overflows, a frequency distribution of the RPNs at each manhole was constructed for the separate categories of "cool spots" and "hot spots". The ABM simulation constructed allowed users to modify the cool spot RPN distribution, hot spot RPN distribution, and the number of hotspots. Therefore, with these parameters, a wide range of risk profiles were possible.

4.5.2.3 Agent behavior guided by metaheuristic search algorithms

Barbati, Bruno, and Genovese (2012) noted that ABMs, due to their promising heuristic techniques that can solve problems with distributed, complex and heterogeneous domains and their ability to translate search algorithms into agent behavior, have been recently used with metaheuristic applications. This capability of ABMs can help in modeling how agents might be allowed to behave, like by moving flow monitors as directed by an algorithm that adapts to the information previously learned by the agents.

In conclusion ABMs are well adapted to model the problem of the risk of failure in sewage systems.

4.6 Development of a simulation

4.6.1 Simulation feature overview

As highlighted previously, the common barriers to the current practices for risk assessment of sewer pipe failure are their high cost and the fact that they cannot account for the dynamic, complex, and unpredictable risks of sewer failure. Hence, agent-based simulation can provide a cost-effective tool to evaluate various approaches to risk assessment.

The model used in this research was based on actual data supplied by City A and was developed using AnyLogic modeling software that provides GIS integration capabilities. The GIS data for City A was available in GIS shapefiles. The shapefiles for pipes and manholes were imported into the model to form the base layer of the environment. From these shapefiles, there were over 14,000 gravity lines and manholes included in the model, representing the complete gravity sewer system in City A. The simulation was built with the option of importing existing risk data from the GIS, such as the classification of failure consequences or the frequency of historical overflows or complaints. Figure (4-20) displays a very small area of the manholes and pipes imported from the GIS system.

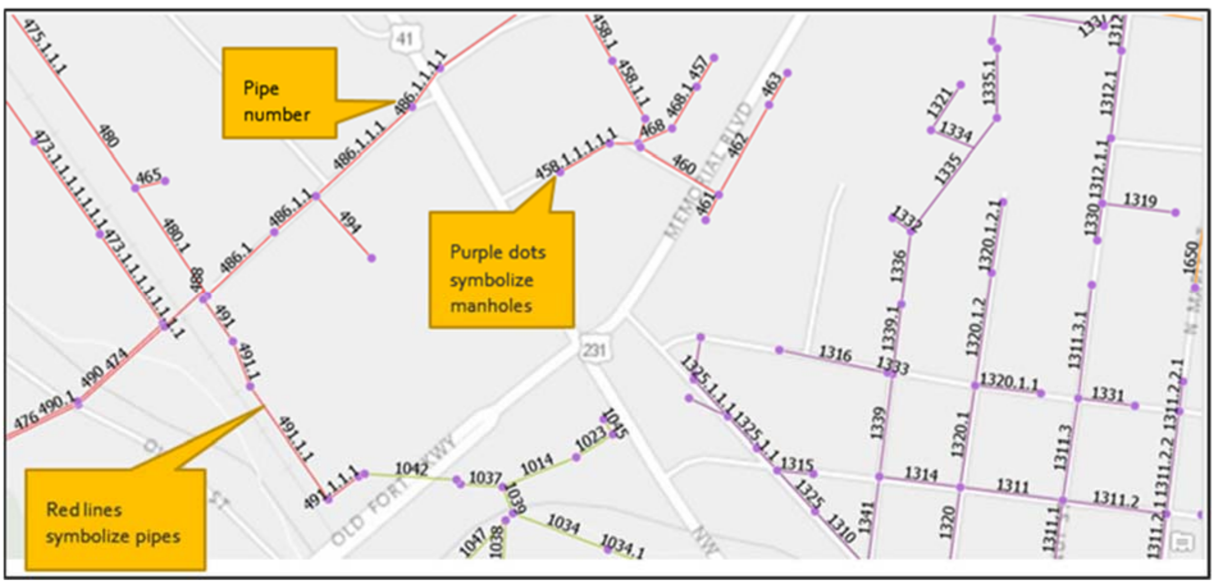


Figure 4-20: An example of the manholes and pipes at City A imported from the GIS system.

The simulation was built with a variety of user-supplied parameters to allow versatility in designing experiments. These parameters include:

1. The number of monitors available. The user may select this number based on the desired trade-off between cost and time.
2. The number of hot spots. The user may select the number of hotspots to be randomly distributed across the system and the size of the hotspots was controlled by a random function based on the analysis of City A hypothesized hot spots and observed historical overflows.
3. Cool spot parameters. The base model distributed the risk outside of hotspots based on a 4-parameter frequency distribution. The user was given the ability to change these four parameters to adjust the intensity and distribution of risks across the pipes that were not in the hot spots. This, for example, provides the ability to simulate isolated pipes that have a high risk of failure.
4. Hot spot parameters. The base model distributes the risk within the hot spots based on a 3-parameter distribution. The user is able to modify the shape, scale, and location of this distribution in order to create a variety of risk profiles within the hot spots.
5. Metaheuristic search algorithm parameters. These parameters are dictated by the search algorithms to be tested. For instance, since the base model implemented a simulated annealing algorithm, the cooling rate was a user-supplied parameter. Furthermore, parameters for defining the neighborhood function of the algorithm, which specifies how far a monitor may be moved in a single iteration, were also supplied.

At run time the environment is built with no two environments being identical due to the random functions built into the simulation. Also, at run time the agents are created and placed at random locations in the environment. In addition, a variety of metrics are maintained as the simulation runs. These include the number of iterations, total cumulative cost, total cost to achieve the constraint, and total duration to achieve the constraint. These are critical process indicators to the performance of the search algorithm.

Figure (4-21) depicts the agents and the environment of a simulation at its termination. The key elements are:

1. The pipe network is displayed by the multi-colored dots that make up most of the image. The dots are colored in clusters depending on their common risk characteristics.
2. The red circles represent the hot spots. The location of the red circles is random based on the number of hotspots parameter. The RPN distribution of manholes within the hotspots is determined randomly based on the three user-supplied hot spot parameters.
3. The yellow circles represent the agents in the model. Agents are used to model locations where sensors are located, and the search algorithm guides the agents to hot spots. In this example, 8 of the 10 agents were within hotspots at the termination of the simulation run.
4. The light green shaded circles represent the neighborhoods of the agents. Therefore, at least an agent is at the center of each green circle and cannot move outside its neighborhood during an iteration.

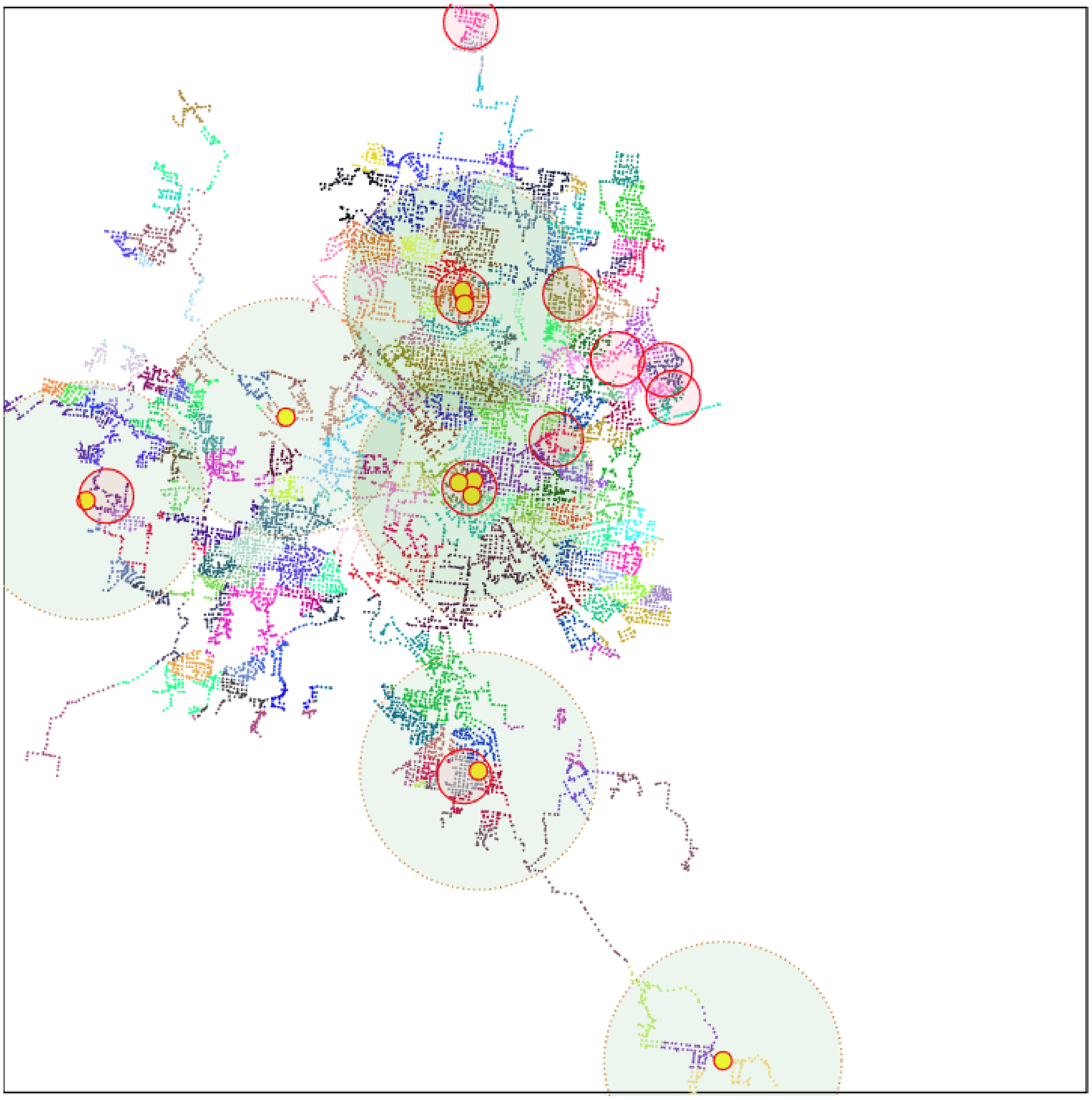


Figure 4-21: Agents and the environment of a simulation at its termination

Figure (4-22) depicts the performance output of a simulation run. There are two charts and 10 process indicators that give insights into the nature of the search. The most important output is the “Cost to achieve minimum RPN threshold”, which is the objective function of the search. The chart in the upper right of the figure, “Threshold RPN per Iteration” is informative for understanding diminishing returns of the search. In this case it is evident that the benefit of additional iterations declined significantly after the 5th iteration, as the slope of the gold line becomes almost flat.

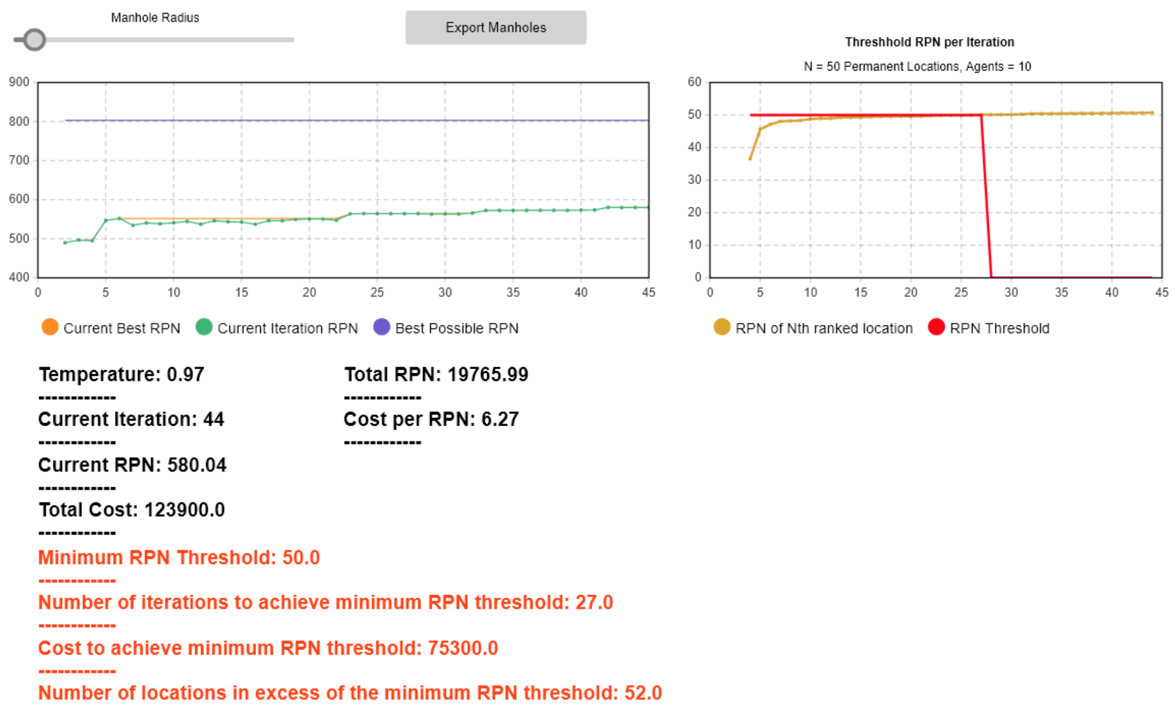


Figure 4-22: Performance output of a simulation run

4.6.2 Importing data from existing GIS files

In this first step the simulation environment, a 2-D map of sewer manholes and pipes, is imported from an existing GIS shapefile. Prior to importing a map, the modeler assigns severity ratings to each manhole in the GIS database and has the option to assign a segmented pipe number that represents the hierarchical relationship of the pipe to other pipes within a neighborhood. These assignments will be stored in the simulation and used in the modeling step. During this step, the user has the ability to import either the entire system or a subset of the system which allows for a more easily managed simulation.

4.6.3 Simulate the distribution of neighborhoods

The adopted simulation model has the capability of either accepting the neighborhoods assigned within the GIS or distributing these neighborhoods probabilistically. In this research, the number of manholes within a neighborhood is represented by an Inverse Gaussian Distribution with a mean of 85 manholes per neighborhood which are taken from an analysis of the modeled system. The frequency distribution of the manholes per neighborhood is shown in figure (4-23) below.

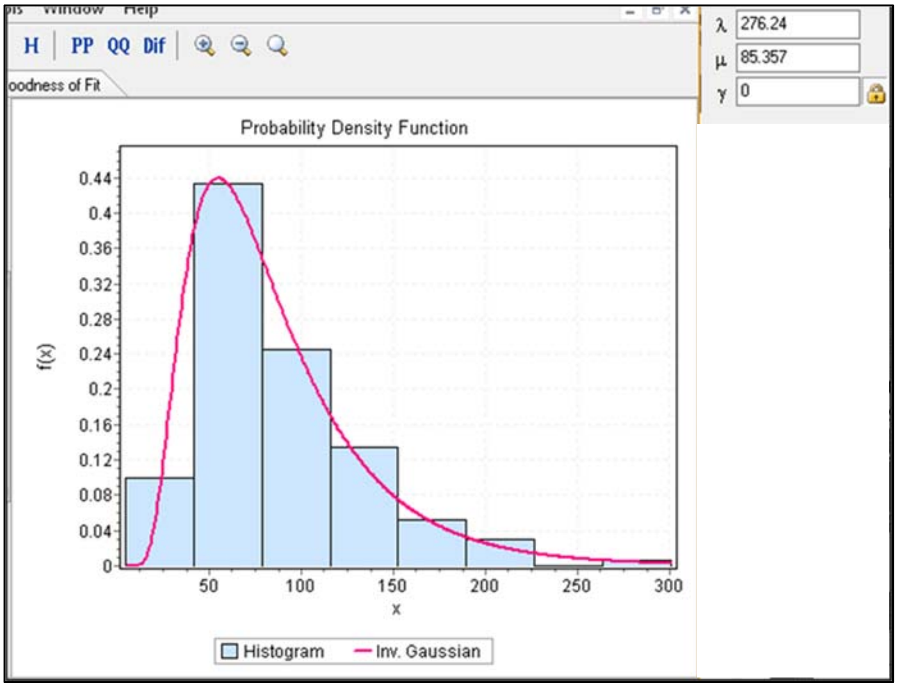


Figure 4-23: The frequency distribution of the manholes per neighborhood

To illustrate the above process, consider a totally synthetic sewer system with manholes distributed as shown in figure (4-24), represented by circles. In this particular system there are 400 manholes connected by pipes. For simplicity, the pipes are not shown.

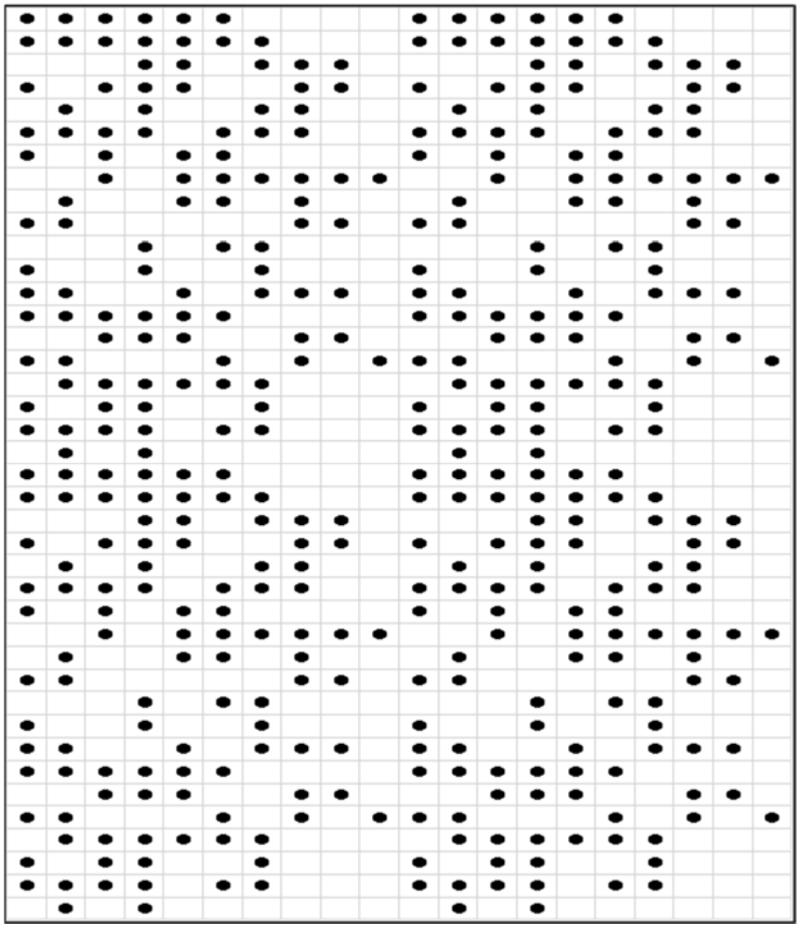


Figure 4-24: A synthetic sewer system

In this system, the simulation model divides the total number of manholes by 85 to arrive at the number of neighborhoods, 400/85 = 5 neighborhoods. Then, for each of these five neighborhoods, a random draw is taken from an Inverse Gaussian Distribution with the shape parameter (λ) = 276.24 and the mean parameter (μ) = 85.357. Consequently, in this example the different neighborhoods take on the following sizes:

- Neighborhood 1 = 46 manholes
- Neighborhood 2 = 69 manholes
- Neighborhood 3 = 151 manholes

- Neighborhood 4 = 71 manholes
- Neighborhood 5 = 63 manholes

Once the neighborhood sizes are determined, the simulation will delineate the synthetic neighborhoods in space by selecting the upper left manhole of each neighborhood on the map. Then, it will select the nearest manholes sequentially until the neighborhood has been filled. For instance, after selecting the manholes for neighborhood 1, the simulation will move to the upper left manhole of the remaining manholes which are not assigned to a neighborhood. Again, the model will select the nearest unassigned manholes in any direction until that particular neighborhood is filled and this process will be repeated until all neighborhoods are filled. Figure (4-25) shows the neighborhood assignments for the synthetic sewer system, each neighborhood is symbolized by a different color dot.

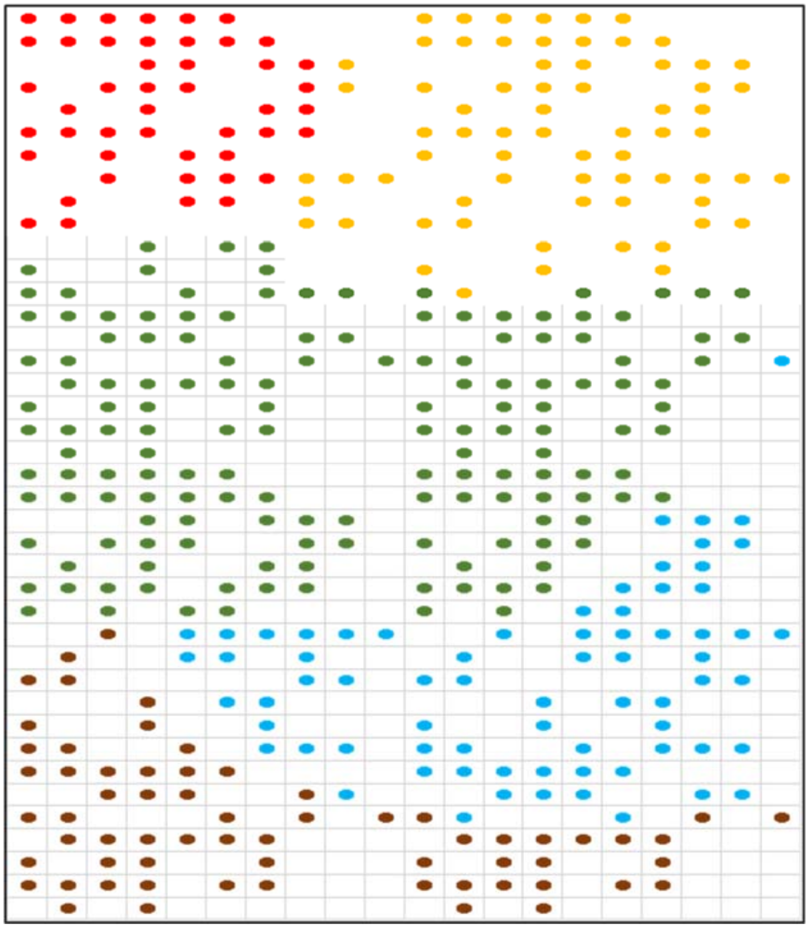


Figure 4-25: Neighborhood assignments of the synthetic sewer system

4.6.4 User-supplied parameters

Although the simulation can generate a wide range of hot spot scenarios, several parameters must be set by the user in order for the model to be able to create a scenario. These parameters are:

1. Number of available monitors. This number may range from a single monitor up to the total number of manholes.
2. Cooling rate. This is the rate used to specify the probability of accepting an inferior solution in the simulated annealing algorithm.
3. Neighbor jump function. The neighbor jump function is a lookup table of RPNs and distances as shown in figure (4-26) which is used to restrict the distance of

movement of a monitor in each iteration. This distance may be defined in terms of a number of neighborhoods away, a number of manholes away, or the maximum distance as the radius in feet.

4. Number of hotspots. The user must specify the number of hotspots to be distributed in the environment which ranges from zero to the number of manholes.
5. Cool spot parameters. Before hot spots are assigned, the simulation will assign RPNs to all manholes based on a Dagum distribution. In order for the simulation to be able to assign these RPNs, the user must specify the following parameters with their default values:
   a. Continuous shape parameter ($k>0$); default = 0.12757.
   b. Continuous shape parameter ($\alpha>0$); default = 44.207.
   c. Continuous scale parameter ($\beta>0$); default = 91.043.
   d. Continuous location parameter (γ); default = -39.454.
6. Hot spot parameters. After the cool spots are assigned, the simulation will assign RPNs to the number of hotspot manholes based on a 3-parameter General Extreme Value distribution. Similarly, in order for the simulation to be able to assign these RPNs, the user must specify the following parameters with their default values:
   a. Continuous shape parameter (k); default = 0.17318.
   b. Continuous scale parameter ($\sigma>0$); default = 1.4409.
   c. Continuous location parameter (μ); default is 47.968.

RPN Range	Maximum movement in any direction		Maximum distance (feet) 0 for no limits
0-10	5	neighborhoods	20000.0
10-20	5	neighborhoods	20000.0
20-30	4	neighborhoods	19000.0
30-40	3	neighborhoods	17000.0
40-50	2	neighborhoods	13000.0
50-60	1	neighborhoods	9000.0
60-70	0	neighborhoods	0.0
70-80	1	manholes	0.0
above 80	1	manholes	0.0

Figure 4-26: Neighbor jump function lookup table

4.6.5 Simulate the distribution of cool spots

The distribution of risk in this study is represented by the distribution of the risk priority numbers (RPN) of each manhole. However, since there is no known historical data set of RPN distribution throughout a wastewater collection system network, multiple methods were used to estimate a realistic distribution based on actual and hypothesized data from an actual system.

Section 4.3.4 describes the method of calculating a hypothetical distribution of RPNs based on risk factors and assigned severity ratings. This produced the distribution of RPNs shown in figure (4-17). A second exercise was conducted using the same assigned severity ratings combined with occurrence ratings from a random sample of 456 locations in 7 different sewer systems as described in section 4.1.3.2.1. A total of 500 RPN samples was created by taking a random draw of occurrence ratings from the 456 locations and multiplying it by a random draw from the 14,496 severity ratings from the studied system. An assumption of independence between severity ratings and occurrence ratings is made. Further investigation would be required to verify actual independence.

Based on the above data, a mixed model that combines both the Dagum and General Extreme Value distributions was created to as a basis for simulating the distribution of RPNs. Figure (4-27) depicts the probability density function of the simulation's default parameters.

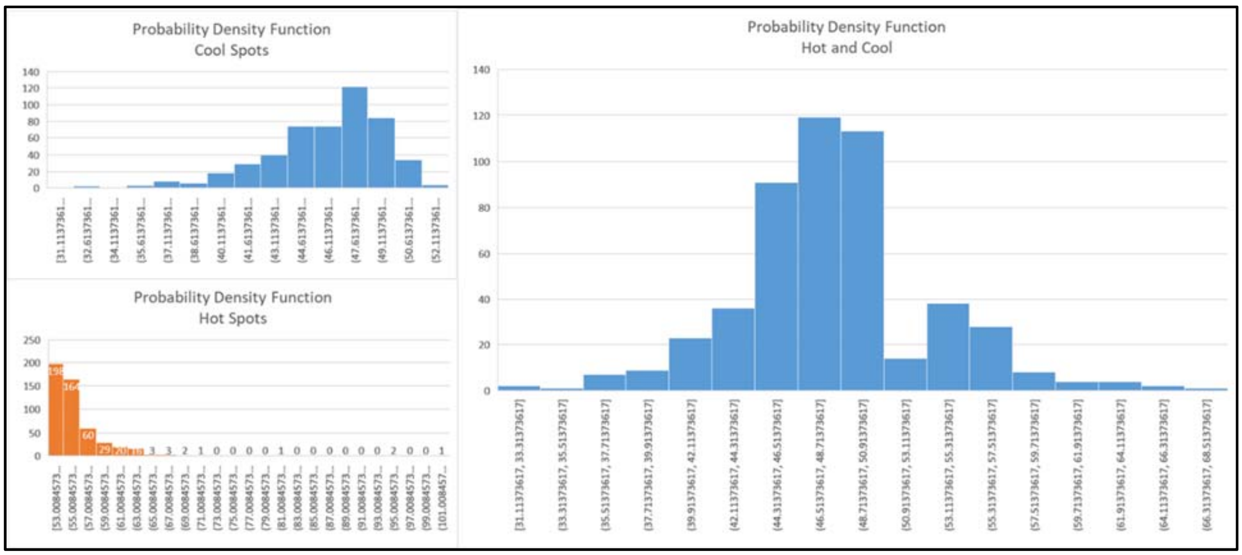


Figure 4-27: The probability density function of the simulation's default parameters

After defining all the required parameters, the simulation will proceed to create the landscape of coolspots and hotspots. The simulation will take a random draw from the Dagum distribution, defined by the user-entered parameters for coolspots, for each manhole in the environment and the RPN for each manhole will be stored as a value for each manhole agent.

4.6.6 Simulate the location and size of hot spots

Following the assignment of the coolspot RPNs, the simulation will start selecting the hotspot manholes. The number of hotspots is determined by the user-defined parameter and the simulation will randomly select that number of neighborhoods from all available neighborhoods from a uniform distribution. A neighborhood may have multiple hotspots that may or may not overlap. In addition, the centroid manhole for hotspots in the selected neighborhoods will be designated as the centroid for the hotspot. In cases where two hot spots are in one neighborhood, the neighborhood will be bisected, and the centroid of each half neighborhood will be the centroid of each hotspot. Neighborhoods with three hot spots will be split into thirds, and so on. Figure (4-28) illustrates two hotspots, symbolized by large blue circles, placed in two neighborhoods of the synthetic sewer system.

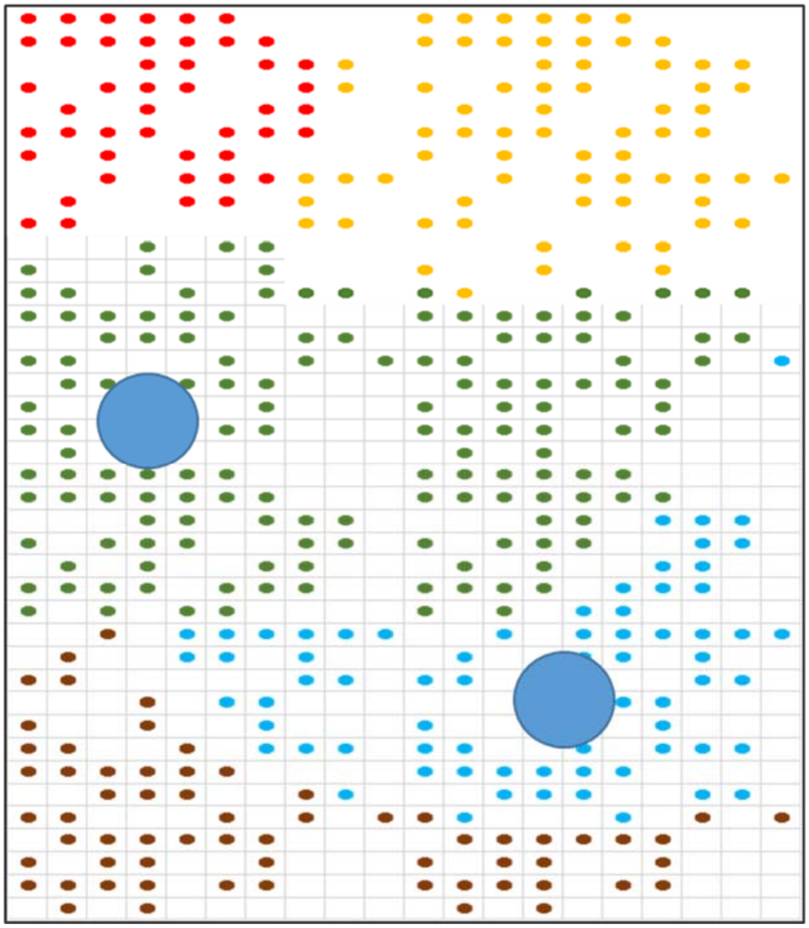


Figure 4-28: Illustration of two hotspots

The size of each hotspot is stochastic. Based on an analysis of the system under study, it is estimated that the number of manholes in each hot spot is a random variable drawn from an Inverse Gaussian distribution with a shape parameter (λ) = 276.24 and a mean parameter (μ) = 73. For each hotspot, a random number is selected from the distribution. In the above example, the first number drawn is 40. Therefore, the first hotspot will be comprised of 40 manholes by progressively extending outward from its centroid until it contains 39 closest neighbors. See figure (4-29). In the case a neighborhood boundary is encountered before the hot spot is filled, the expansion of the hot spot will be held within the neighborhood. If there are not enough manholes in the neighborhood to fill the hot spot, the entire neighborhood will be selected. If there is more than one hot spot in the neighborhood, a manhole may be contained within multiple hot spots.

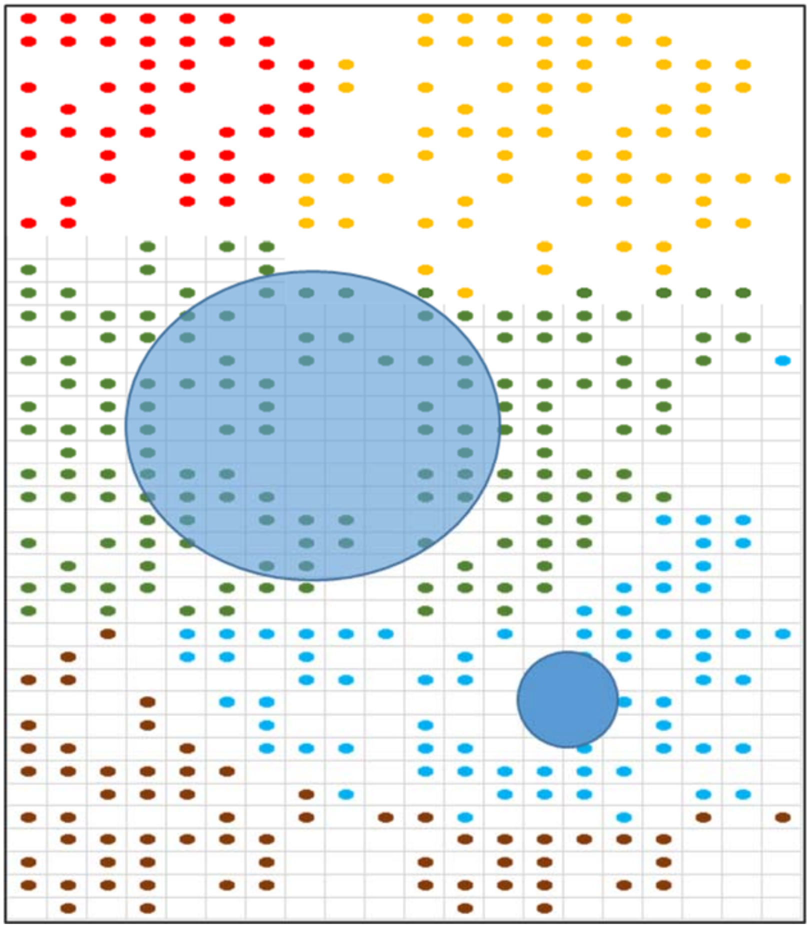


Figure 4-29: Illustration of the size determination of the hotspots

4.6.7 Simulate the distribution of hotspot RPNs

Once selected, the simulation will update the RPN's of the hotspot manholes based on a random draw from the General Extreme Value Distribution defined by the user-entered parameters for hotspots. Manholes that are in more than one hot spot may have the RPN values updated several times, retaining the last RPN assignment made.

4.6.8 Hotspot seeding capability

Utility managers may be aware of hot spots in their system. The simulation was designed to allow the modeler to specify some or all the initial locations of the agents within hotspots to study their impact on convergence. To enable this feature, a new user-supplied parameter, known_hotspots, was added. During the simulation initialization, a number of agents, equal to the known_hotspots parameter, are placed randomly within the radius of hotspots. The simulation allows more than one agent to be located within the same hotspot so long as they follow the rules for manhole separation. For illustration, the map in figure (4-30) depicts 10 agents and 28 hot spots. Assuming that the known_hotspots parameter was set as a value of eight, then eight of the agents are randomly placed within the radius of at least one hotspot. This will be the starting assignment for iteration 0 and the simulation progresses as usual from this placement based on the chosen search algorithm.

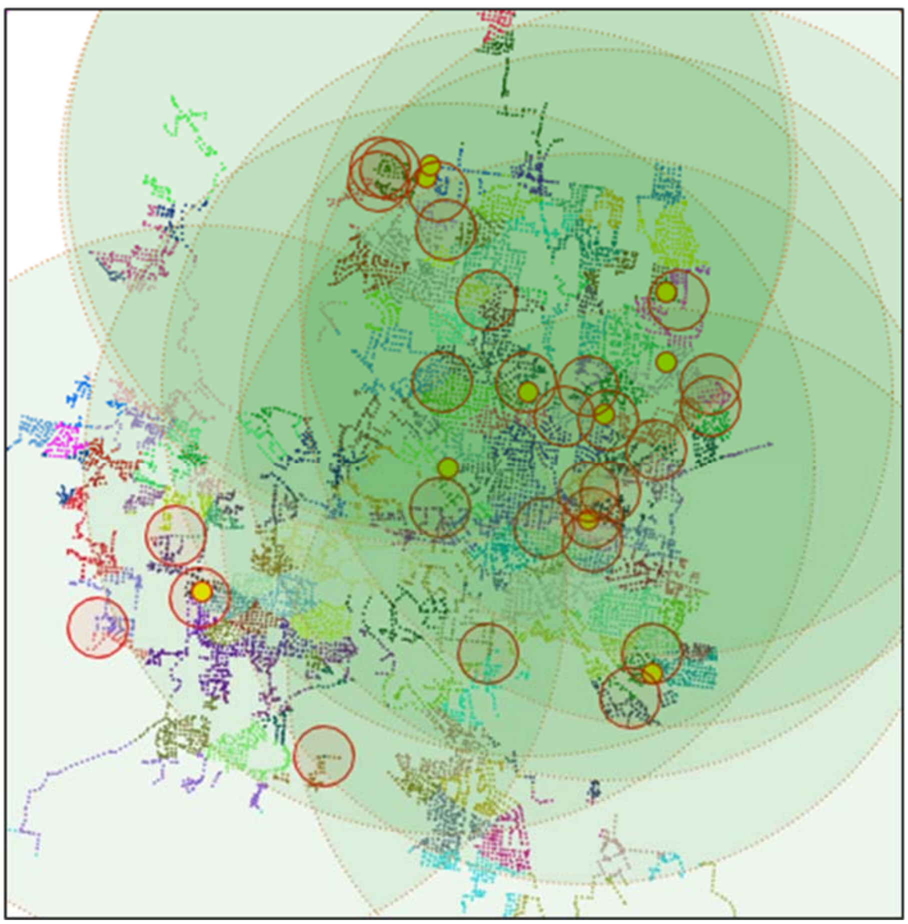


Figure 4-30: Map of known hotspots

4.6.9 Simulation of the distribution of severity ratings

The severity ratings produced as part of the FMEA analysis are critical inputs to the enhanced simulated annealing algorithm. The simulation provided the ability to import severity codes from the assignment in the GIS or to assign then probabilistically to test the robustness of the search techniques.

4.6.9.1 Initialize severity codes

This step is only needed when assigning the severity codes probabilistically in which each manhole is assigned a severity code during the initialization of the simulation. The assignment is based on a random draw from a Weibull distribution whose parameters vary depending on the RPN of the manhole. The process of assigning these codes uses the following steps:

1. RPNs are assigned to manholes as described previously depending on hot spot and cool spot parameters.
2. The model will read the assigned RPN for each manhole, then calculate the respective severity codes as follows:
    a. Take a random draw from a uniform distribution between 0 and 1.
    b. Calculate the inverse cumulative distribution function of the 2-parameter Weibull distribution using the random number as the P parameter. The inverse cumulative distribution function of the Weibull distribution is given as:

$$F^{-1}(P) = \beta(\ln\frac{1}{1-P})^{1/\alpha} \tag{4-12}$$

where the values of α and β are determined based on the RPN of the manhole as per table (4-13) below.

Table 4-13: Values of α and β

RPN Bin	α	B
0-10	1.4535	2.0464
11-20	2.5256	5.6684
21-30	4.3503	8.2735
31-40	10.949	8.6302
41-50	15.555	8.5674
51-60	16.584	8.8456
61-70	22.702	9.2171
71-80	23	9.5 (estimated all values are 9)
> 80	23	9.5 (estimated no RPNs > 80)

a. Assign the result of the inverse cumulative distribution function as the severity code of the manhole. This code should be a number between 0 and 10 and any results greater than 10 are rounded down to 10.

4.6.9.2 Graphical Depiction

The graph of the inverse of the cumulative distribution function of the Weibull distribution along with empirical data in the 50-60 RPN bin is shown below in figure (4-31). The empirical data comes from City A, where severity codes were assigned using the scoring rubric and occurrence codes were estimated based on reported overflow analysis. Although the fits are approximate, they are felt to be sufficient based on; a) the approximate calculations are adequate for the simulated environment; b) use of a consistent distribution across all RPN bins is desirable; c) ease of implementation of this feature for development of the simulation tool is perceived as important.

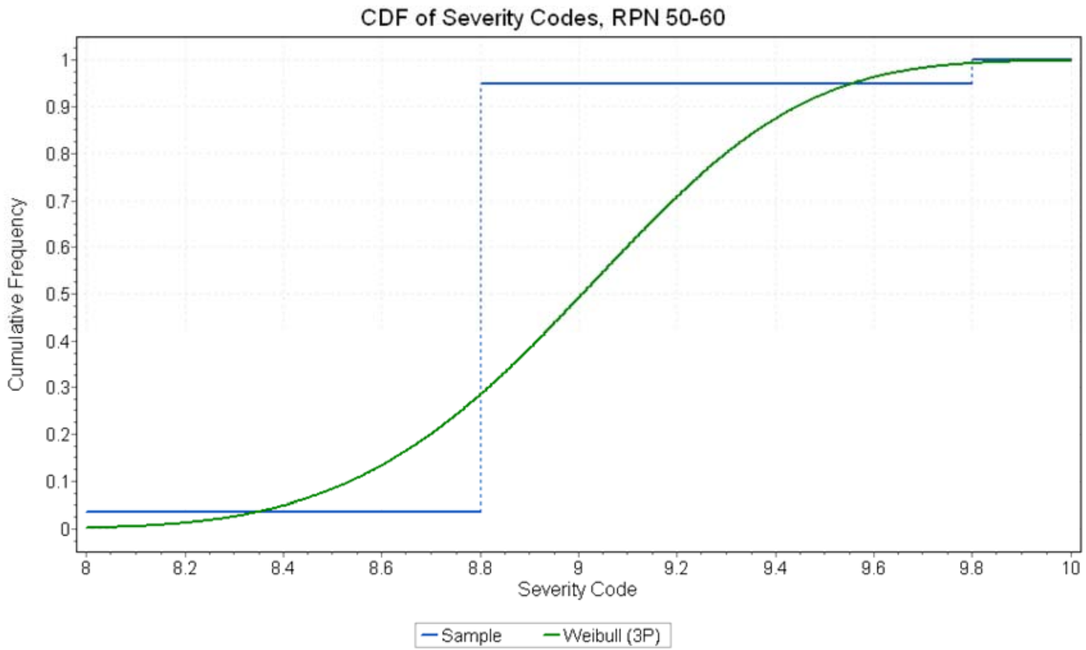


Figure 4-31: Graphical representation of the severity code cumulative distribution function

4.6.10 Implementation of search algorithms in the simulation

A major goal of the simulations was to test the performance of various search algorithms in terms of the objective function. Four search techniques were implemented in the simulation:

1. Base simulated annealing. This is an unembellished simulated annealing algorithm that does not consider the peculiarities of the structure of the problem.
2. Enhanced simulated annealing. Several enhancements were tested in the quest for making improvements to the performance of base simulated annealing.
3. Sequential search. Sequential search mimics a common practice in inspection techniques to assess risk in sewer networks. It was used as a

baseline to contrast the benefits of metaheuristic search to an exhaustive search methodology.

4. Greedy search. Another baseline to contrast the benefits of local-optima-escape features of simulated annealing.

The following sections will describe the operation of each agent movement technique.

4.6.10.1 Base simulated annealing

Figure (4-32) summarizes the logic used in the base simulated annealing algorithm when the jump function is neighborhoods. It is worth noting that if the jump function is in manholes, then agent movement is upstream or downstream on a particular pipe within the limits of the number of manholes specified. If the jump function is in feet, then agent movement is a random selection of a location within a circle with the radius provided by the user.

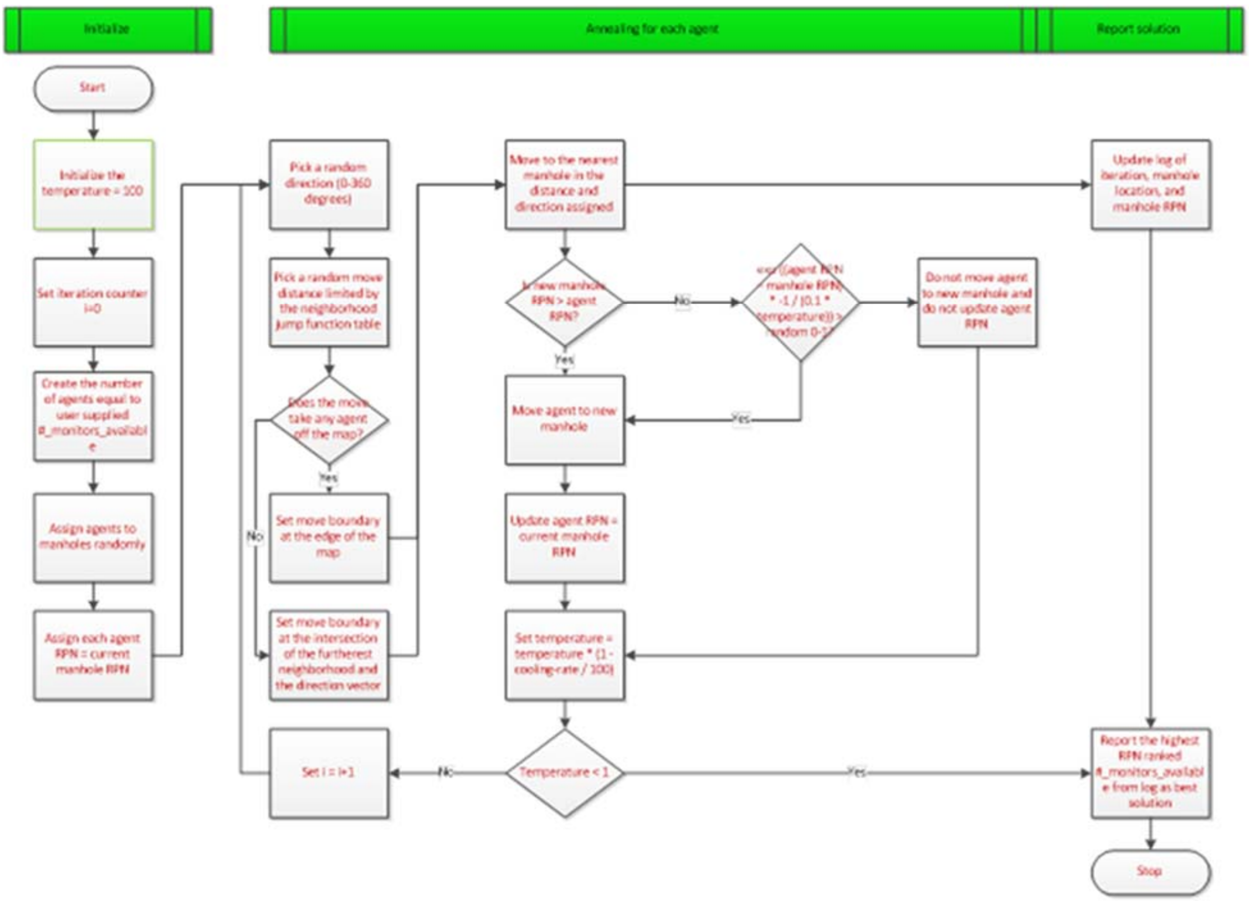


Figure 4-32: Flowchart of the logic used in the base simulated annealing algorithm

Several variables that were used in the base annealing algorithm are defined within the simulation before initializing, these variables are:

- Agent_rpn. The RPN of the monitor that is subject to change at every iteration.
- Manhole_rpn. The RPN of the manholes created during the initialization of the environment.
- Iterations (i). The counter for the number of time steps that have been simulated.
- Iteration_rpn. The sum of all Agent_rpns for the current iteration.
- Best_rpn. The best solution that has ever been found during the progress.

- Best_manholes. The manhole numbers that achieve the Best-rpn.
- Temperature (t). Starts at 100 and the algorithm terminates when it gets below 1.
- Best_possible_RPN. The global maximum solution which will be rarely discovered by the algorithm.

4.6.10.1.1 Initialize the annealing

To begin the simulated annealing run, iteration is set to i = 0 and Temperature is set to t = 100. At the completion of each iteration, (i) is incremented by 1 and (t) is reduced as a function of the user supplied cooling rate. The simulation will halt when the temperature falls below 1 or when there are no more allowed locations for agents to move to.

A number of agents will be created equal to the user supplied #_monitors_available parameter. Each agent is assigned to a manhole randomly based on a uniform distribution and all the manholes on the map have an equal chance of being selected as an initial monitoring location. In the example shown in figure (4-32), there are 2 agents, representing 2 monitors, and 400 manholes. Thus, for each monitor a random number between 1 and 400 is drawn from a uniform distribution and Agent 1 is randomly assigned to manhole 201 and Agent 2 is randomly assigned to manhole 83. Furthermore, the Agent_rpn variable is updated to be equal to the Manhole_rpn of the assigned manhole. In the example, Agent 1 takes on the RPN of 40 from manhole 201 and Agent 2 takes on the RPN of 32 from manhole 83. Afterwards, the variables Best_rpn, Best_manholes, and Best_possible_RPN are updated for the first time as shown in figure (4-33).

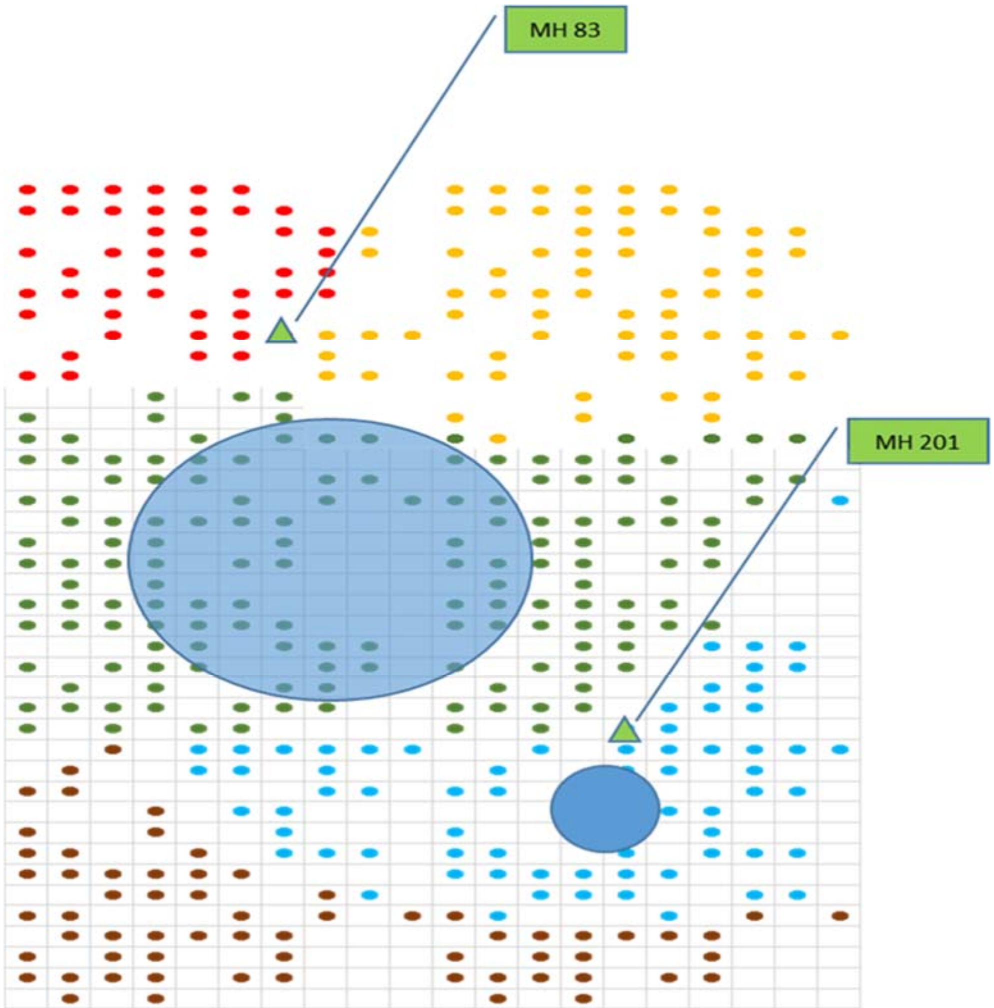


Figure 4-33: Initializing the base annealing model

4.6.10.1.2 Calculate move direction and distance

The move direction and distance operate with some minor differences depending on the jump function. However, in all cases the principle is to define a subset of valid moves (i.e. "neighbors") and select a candidate location from among this subset.

4.6.10.1.2.1 Movement when the jump function is neighborhoods

The move direction and distance for each agent are calculated independently. Regarding the move distance, a random direction between 1 and 360 degrees is selected from a uniform distribution. In the example illustrated in figure (4-34), the random direction was 259 degrees for Agent 1 and 59 degrees for Agent 2 which are shown as green vector lines on the illustration with the current Agent locations as the origin.

With regards to the move distance, a number of steps are performed to calculate this parameter. First, a maximum move distance is derived for each agent from the number of adjacent neighborhoods provided by the neighbor jump function table and depending on the RPN number of the origin location. Second, the move distance becomes shorter as the RPNs increase under the assumption that higher RPNs are near hot spots and monitors should stay close to hot spots and it may be limited by the map size. Third, boundaries are set as points on the direction vector where either the furthest allowed neighborhood or the map boundary intersects the vector. For instance, if an agent is allowed to travel three neighborhoods away, then the maximum move distance is the distance between the current monitor location and the intersection of the direction vector and the furthest boundary of the third neighborhood along the direction vector. Fourth, the distance between the origin point and boundary point is then calculated using the Pythagorean Theorem. Fifth, the actual move distance is selected randomly from a uniform distribution between 1 and the maximum move distance. Finally, the nearest manhole along the direction vector at the move distance is then selected. It is unlikely that there will be a manhole at the exact coordinates of the move direction and distance, therefore the nearest manhole is selected. In the example, both agents would be allowed to move up to three adjacent neighborhoods away along the direction vector, so long as they do not reach the end of the map. The boundary is the intersection of the green direction vectors and the thick red map boundary lines. Consider Agent 1 located at (x,y) = (15, 14), with a boundary at the map limit of (1, 9).

The maximum move distance is 14.87 and the random draw from the uniform distribution between 1 and 14.87 was selected as 10.7. Consequently, Agent 1 will be placed approximately at (4.9, 10.4) and the nearest manhole is depicted by the brown circle immediately to the left of (4.9, 10.4) as shown in figure (4-33).

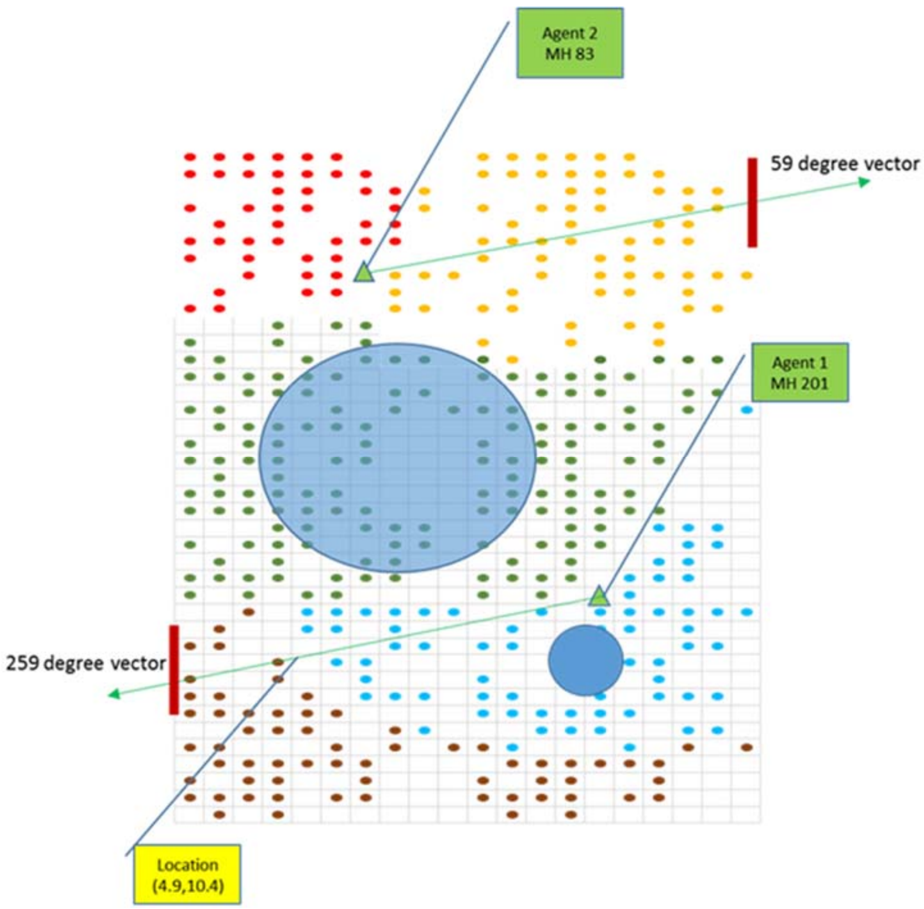


Figure 4-34: The move direction and distance for Agent 1

4.6.10.1.2.2 Movement when the jump function is distance

In this case, the movement distance is a function of RPN as was the case when the jump function was neighborhoods. However, when the distance is specified in feet the candidate locations are the set of all manholes within the distance given in the table in any direction. The actual move is selected randomly from the set of candidate locations with each location having an equal probability of being selected. Once a location is selected, the move is tested as an agent may or may not actually make the move depending on two tests.

The first test states that if the destination Manhole_rpn is greater than the current Agent_rpn, then the agent will always make the move. The second test allows an Agent to move to a lower RPN depending on the temperature calculation. The purpose of this test is to allow Agents to escape local maxima in early iterations. However, because the destination RPN is lower, the move will be subject to the temperature test which follows the Boltzmann distribution using k = 0.1 as the Boltzmann constant. Thus, the formula for the test to accept the move to a lower RPN is:

$$\mathrm{Exp}((\mathrm{Agent\_rpn} - \mathrm{Manhole\_rpn}) * -1 / (0.1 * \mathrm{temperature})) > \mathrm{rand}(0,1) \qquad (4\text{-}13)$$

This is illustrated in the example when considering Agent 1 that has an Agent_rpn of 40 that it inherited from being assigned to manhole 201. Its destination is determined to be manhole 290, which has a Manhole_rpn of 35. Consequently, the temperature test is performed which yielded the following result:

$$\mathrm{Exp}((40 - 35) * -1 / (0.1 * 100)) > 0.45, \text{ or } 0.60 > 0.45 = \mathrm{TRUE}$$

Therefore, the move is accepted to the new manhole 290.

Once all the moves are tested, agents that have destinations with higher RPNs or that pass the temperature test are moved. Those which fail remain in their current location. Figure (4-35) shows the movement of Agent 1 to its new location at manhole 290.

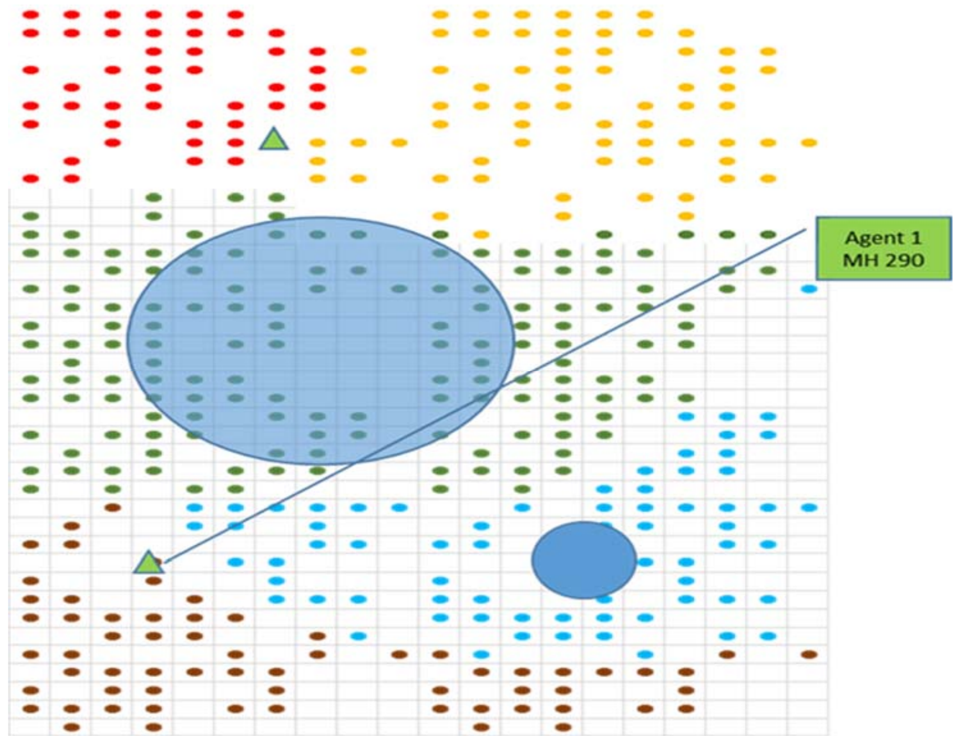


Figure 4-35: Movement of Agent 1

After the movement is completed, the logs of manholes, iterations, and RPNs are updated with the results from the iteration. For example, Manhole 201 – iteration 0 = 40 and Manhole 290 – iteration 1 = 35. The temperature is then reduced by setting temperature = temperature * (1 – cooling_rate / 100). If the new temperature is below 1.0 then the simulation terminates. Otherwise the iteration is set to = iteration + 1 and the annealing process is performed repeatedly until the temperature is reduced below 1.0.

4.6.10.2 Enhanced simulated annealing

The idea behind enhancing the base simulated annealing algorithm is primarily to take advantage of the knowledge of the consequences of pipe failure to favor the selection of high-overflow-consequence manholes, i.e. the manholes with high severity ratings. This enhancement requires that severity ratings be stored in a GIS attribute, sev_code, based on the severity rating rubric. Then the sev_code variable is imported into the simulation. The enhancement also implements a user-defined variable, sensor_range, to allow users to specify how many manholes a single monitor can "sense". For instance, a single monitor may detect failures at two manholes upstream and downstream of its location. It would be redundant to place another monitor within two manholes. Figure (4-36) shows the flowchart of the operation of the enhanced simulated annealing algorithm.

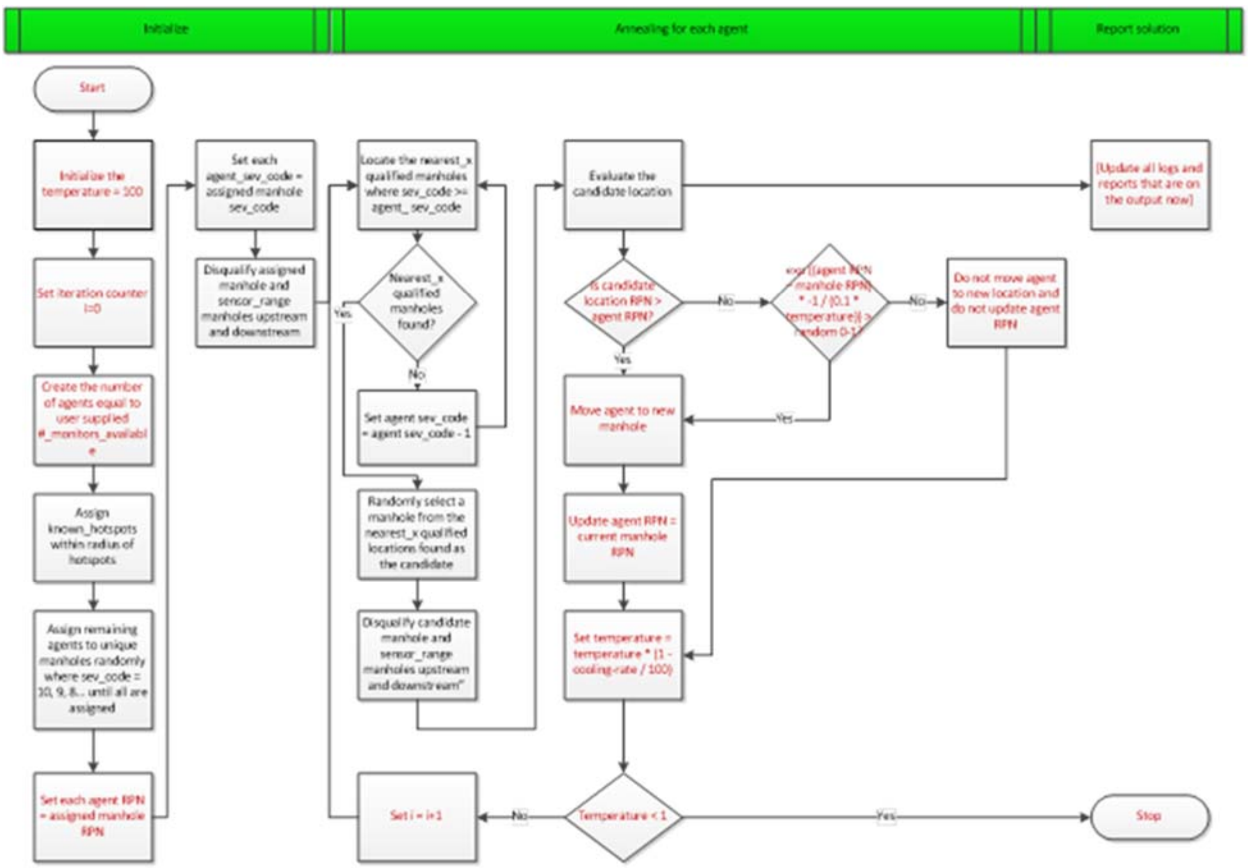


Figure 4-36: Enhanced simulated annealing algorithm

4.6.10.2.1 Initial assignment of monitors to manholes

In the enhanced algorithm, agents are assigned to manholes in sev_code priority ranking. The known hotspots quantified by the parameter "known_hotspots" occur before agents are assigned in any other manner during initialization. Then, the remaining agents are assigned in order of manhole sev_code. This process begins by attempting to assign all unassigned agents to manholes with a sev_code = 10. If there are more unassigned agents than manholes with sev_code = 10, then agents will be assigned to every manhole with sev_code =10 before moving to the next sev_code = 9 and this loop continues until all agents are assigned to a manhole while the rules preventing more than 1 agent visiting a particular manhole are still in place. Once agents are assigned to manholes, the sev_code of the manhole is assigned to agent_sev_code. This update of the variable agent_sev_code is a unique feature of the enhanced simulated annealing algorithm.

Any particular manhole can only be evaluated once during a simulation run. An agent is prohibited from evaluating a manhole that has been previously evaluated. In addition, an agent may not evaluate any manholes within the user-supplied "sensor_range" of manholes upstream or downstream. Consequently, those manholes which have not been previously evaluated by an agent nor have they been within the "sensor_range" of an evaluated manhole will be labeled as "qualified".

4.6.10.2.2 Selection of candidate locations for movement

Unlike in the base algorithm, the enhanced algorithm implements the concept of "nearest x" manholes in which the value of "x" in the neighbor jump function is defined by the modeler at initialization. This difference in selecting the candidate locations for movement is illustrated in figure (4-37).

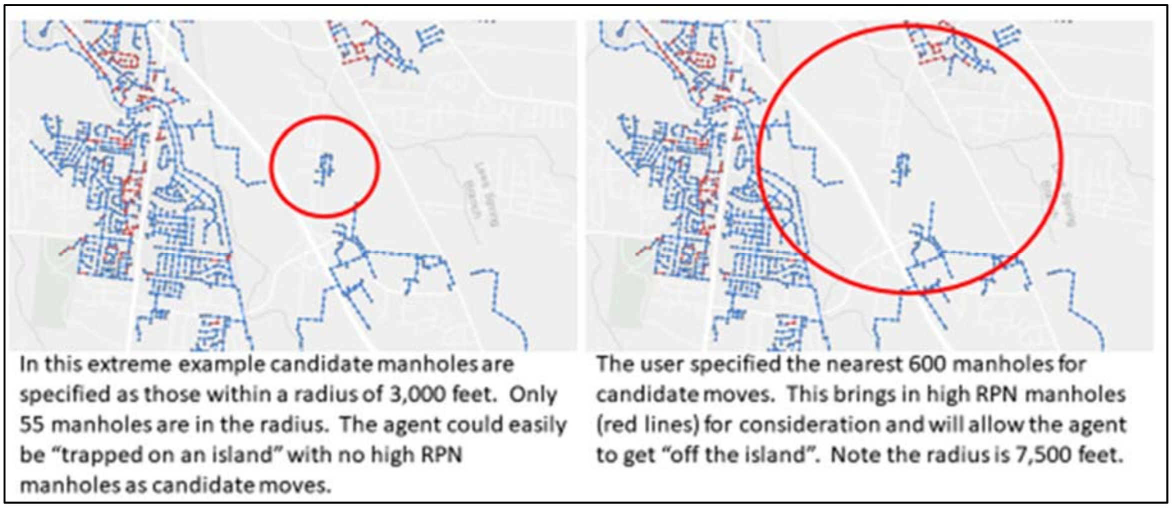


Figure 4-37: Nearest x Manhole vs. Fixed Distance

This algorithm is based upon the observation that locations with high RPNs are more likely to have high sev_code values and more likely to be in close proximity of other high RPN locations. Table (4-14) demonstrates the strong correlation between the severity ratings and the proportion of locations with RPN values above the risk threshold of 50 based on estimates in City A.

Table 4-14: Correlation between severity codes and high RPNs

Sev_code	**Number of Locations**			
	RPN < 50	**RPN >= 50**	**Total**	**Percentage >= 50**
0	1		1	0.0%
1	350		350	0.0%
2	120		120	0.0%
3	421		421	0.0%
4	265		265	0.0%
5	623		623	0.0%
6	2		2	0.0%
7	3		3	0.0%
8	7,750	823	8,573	9.6%
9	3,171	1,056	4,227	25.0%
10	17	16	33	48.5%
Total	12,723	1,895	14,618	13.0%

4.6.10.2.3 Agent movement

A fundamental change in this algorithm compared to the base simulated annealing is the prioritization of the search by sev_code. Therefore, to begin the search loop, each agent will start locating the nearest_x qualified manholes where sev_code >= agent_sev_code as illustrated in figure (4-38). In this figure, each circle represents a manhole, the upper number is the sev_code while the bottom number is the RPN.

In this example, the agent begins at the purple manhole with a sev_code of 10 and an RPN of 50. The purple manhole is disqualified from being evaluated again during the simulation run. The nearest_x is assumed to be 3 for all RPN values. Note the simulation allows the user to enter up to 9 different values for nearest_x depending on the value of the agent's RPN. The agent_sev_code = 10, indicating the search will begin with only manholes that have a sev_code = 10.

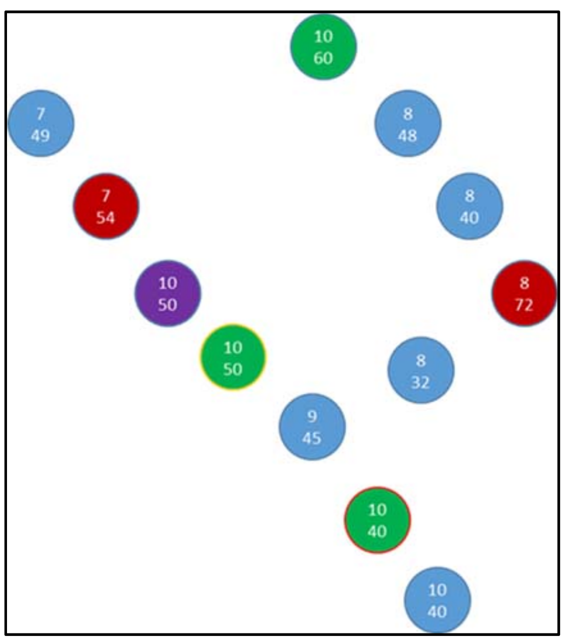


Figure 4-38: Initial search states for the enhanced model

From the inspection, the nearest manholes that have a sev_code >= 10 are the ones shaded green. A random selection is made from among these 3 candidates and the manhole with sev_code = 10 and RPN = 40, represented by the red circle shaded green, is selected for evaluation as shown in figure (4-39). Aside from the first assignment, the evaluation proceeds as before with higher RPN locations always accepted for move while the lower ones are accepted based on the probability calculation explained earlier. As a result, in this example, the candidate RPN of 40 is lower than the agent RPN of 50 so there is no automatic move. However, it is assumed that the probability calculation allows the movement to a lower RPN.

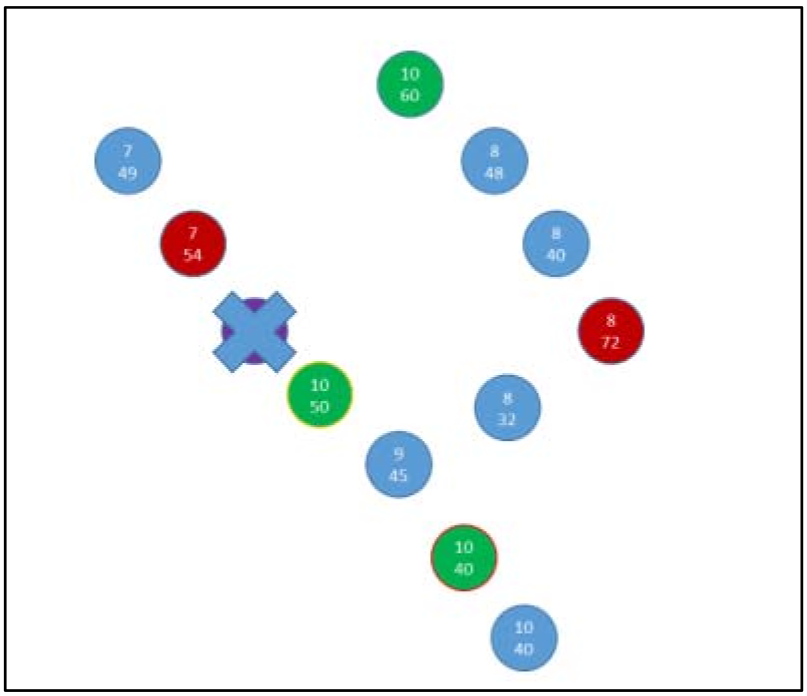


Figure 4-39: Updated search

It is important to note that the progress of the algorithm is based on the evaluated manholes, regardless of whether an agent moved to them. In the example, the log will show two manholes evaluated, the purple one with an RPN of 50 and the red circled one with an RPN of 40. They are no longer qualified for future selection during the simulation run.

Next, the search progresses looking for 3 manholes with sev_code >= 10, the agent_sev_code. Three qualified manholes are available, therefore one of them will be selected randomly for evaluation, the manhole with a yellow circle. This manhole has a sev_code = 10 and RPN = 50. Since the RPN is higher than the agent RPN, the move is accepted without further testing. Two manholes are now disqualified as depicted in figure (4-40).

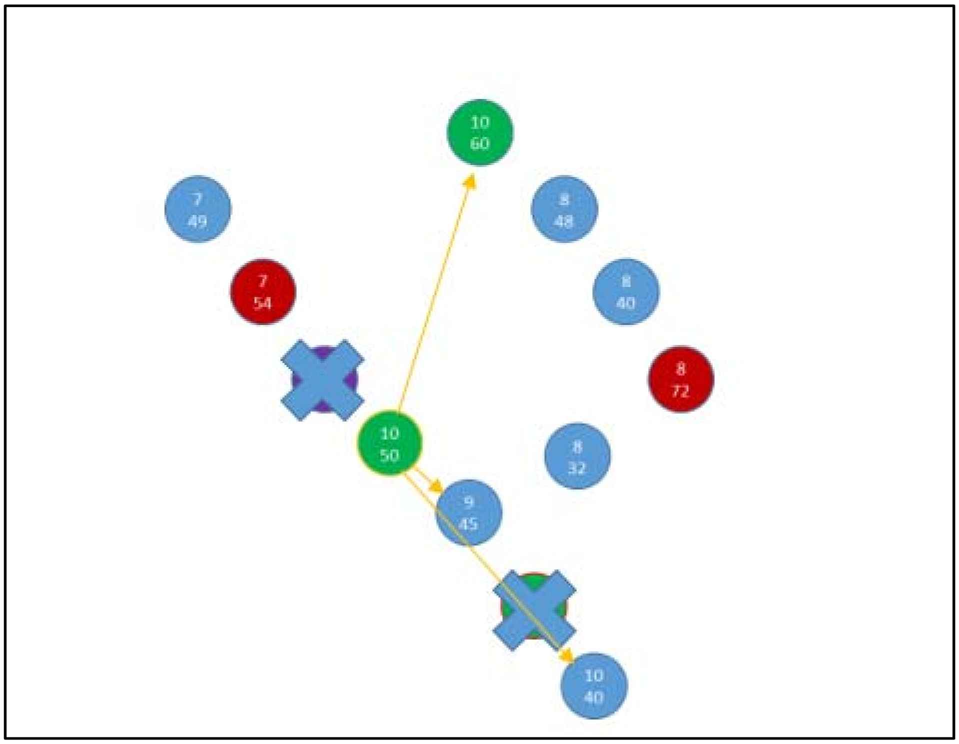


Figure 4-40: Progressed search

Similarly, the search will continue looking for the 3 nearest manholes with sev_code >= 10. However, since there are only 2 qualified manholes that meet this condition, the agent_sev_code is decremented by 1 and set to 9. The search now looks for the 3 nearest manholes with sev_code >= 9, shown by the yellow lines in figure (4-39). One of the candidates from among the 3 is selected at random and the search continues until the temperature becomes <= 1.

4.6.10.3 Sequential search algorithm

The sequential search algorithm is designed to mimic the heuristics commonly used in a large-scale closed-circuit television (CCTV) project. In this algorithm, inspections start at the top of a collection system and work downstream. This means that lateral lines are inspected first, then followed by mains, trunks, and interceptors. The rationale for adopting this algorithm is that pipes are usually cleaned before inspection by CCTV. During cleaning, debris is flushed into progressively larger pipes and ultimately to the treatment plant. So, since bigger lines have higher scouring velocity that aid in the flushing of debris, they should be inspected last. When a pipe junction is reached, inspectors will move to the top of other lines coming into the junction and work back downstream to the junction. A high-level flowchart of the algorithm is presented in figure (4-41).

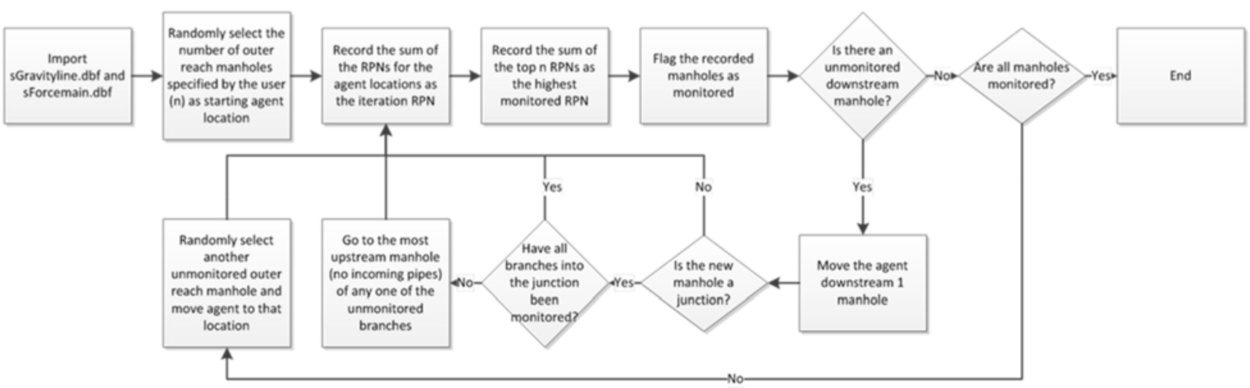


Figure 4-41: Sequential search algorithm flowchart

As seen from the above flowchart, a new parameter, which is number of inspectors (#_inspectors), is added to accommodate sequential search which will be specified by the user in a range from 1 to 30.

4.6.10.3.1 Errors in GIS database

The sequential search algorithm requires that all pipes in the sewer network be connected to nodes (manholes) so that agents can move from an upstream terminal node to a downstream terminal node. It is common for GIS systems to contain errors in connectivity of the network. Therefore, to resolve this issue, the simulation has the capability to optionally process corrections of errors and omissions in the imported databases. This capability allows the user to create an Excel workbook referencing the upstream and downstream manholes as stored in the GIS with values to update either of them. The workbook may also delete records from the GIS. An example of this capability is given in table (4-15). As seen from the table, the first row updates the upstream manhole. The second updates the downstream manhole. The third row deletes the first record that matches the US_Manhole and DS_Manhole as it is possible that the GIS database contains more than one record with the same US_Manhole and DS_Manhole. In that case only the first record is deleted. If the user wants to delete additional instances of that manhole combination, then the Excel workbook must contain multiple rows specifying the given manhole combination with the "Delete 1st_Record" field set to "Y".

Table 4-15: Example of the capability to correct errors in the GIS database

US_Manhole	**DS_Manhole**	**New_US_Manhole**	**New_DS_Manhole**	**Delete 1st Record**
021B024B	012B024A	012BO24H		
074A001B	074A001B		074C0080	
075C0090	075C0080			Y

4.6.10.3.2 Initializing the sequential search algorithm

The sequential search algorithm utilizes the same variables as described previously except that the temperature is unnecessary. At the outset, the number of agents is created equal to the user supplied #_inspectors parameter. Each agent is assigned respectively to the manholes furthest from the centroid of the map that are also “terminal manholes”, which are manholes at the upstream of pipes with no pipes entering them. The first agent is assigned to the furthest manhole from the centroid, the second agent is assigned to the second furthest manhole from the centroid of the map… etc. Figure (4-42) illustrates the assignment of four inspectors.

Figure 4-42: Assignment of inspectors

4.6.10.3.3 Agent Movement in the sequential search algorithm

For each agent, moves are evaluated independently at each iteration. An iteration is complete when every agent moves to a new qualified manhole. The designation of upstream and downstream manholes is contained in the merged database of the sGravityline and sForecemain tables from ArcGIS, after corrections. In general, an agent will move downstream as long as the downstream manhole has not been previously monitored. There are two exceptions to this rule, namely: 1) A junction is reached where more than one pipe enters a manhole, and, 2) There are no unmonitored manholes downstream. Table (4-16) summarizes the rules for movement, with a small-scale example presented in figure (4-43).

Table 4-16: Rules of movement in sequential search algorithm

Is there an unmonitored downstream manhole?	Is the new manhole a junction?	Have all branches into the junction been monitored?	Have all manholes been monitored?	Action
Yes	Yes	Yes	-	Accept the downstream manhole as the location for the next iteration
Yes	Yes	No	-	Locate the agent at the most upstream manhole of any one of the unmonitored branches
Yes	No	-	-	Accept the downstream manhole as the location for the next iteration
No	-	-	Yes	End of the run
No	-	-	No	Randomly select another unmonitored outer reach manhole and move the agent to that location

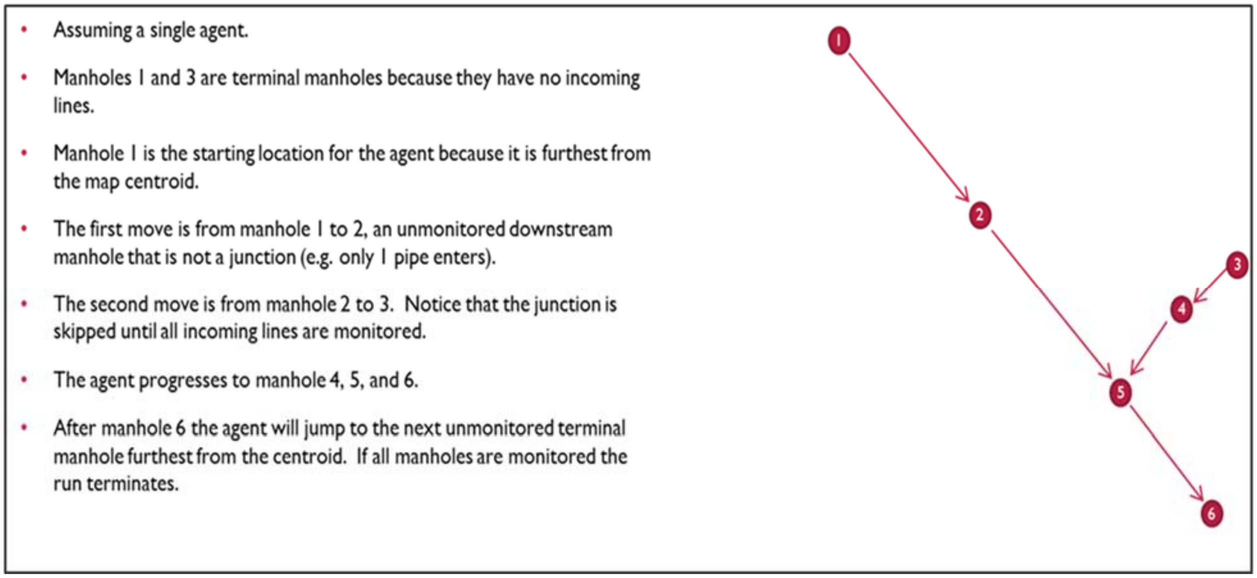


Figure 4-43: Example of agent movement in sequential search algorithm

4.6.10.4 Greedy algorithm

A greedy algorithm is one that only accepts moves that improve the objective function. In the context of this research, it is an algorithm that allows an agent to move only to candidate locations with equal or higher RPN. The purpose of this algorithm is to compare the efficiency of the simulated annealing and enhanced simulated annealing algorithms against the greedy search algorithm that always rejects inferior moves. Consequently, for the ease of development, the greedy algorithm implemented in the simulation makes two simple changes to the simulated annealing algorithm:

1. The temperature variable is set to a fixed value of 0.0001. This temperature value is held constant throughout the simulation and not affected by the cooling rate. This effectively sets the Boltzmann factor equal to zero meaning that there is a zero chance that an agent will accept an inferior move.
2. The stopping criteria is modified to stop after 120 iterations (10 years of iterations). Figure (4-44) illustrates the operation of the Greedy Algorithm.

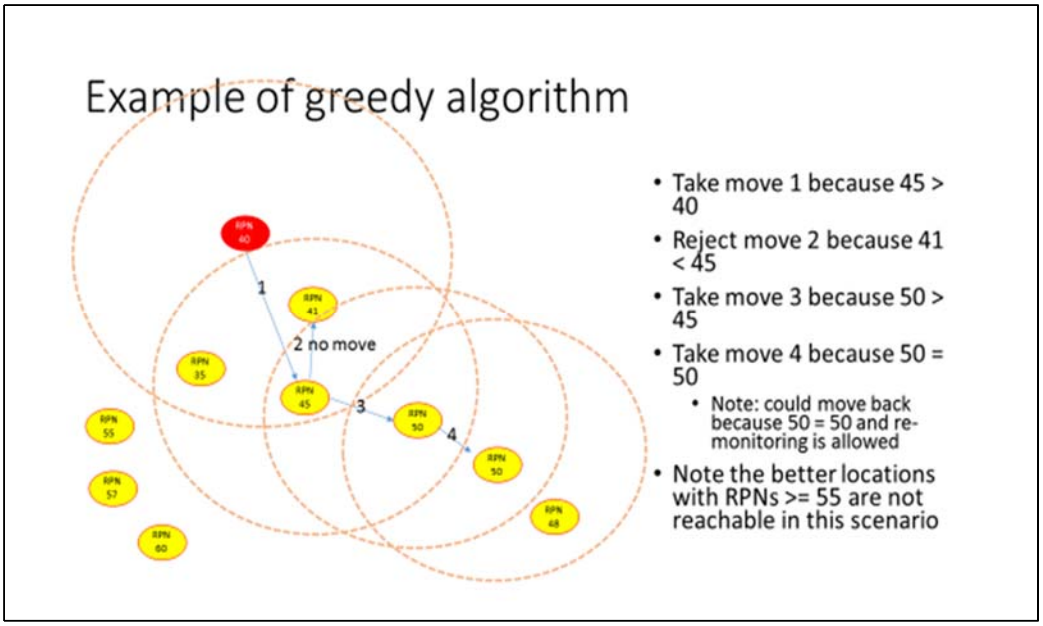


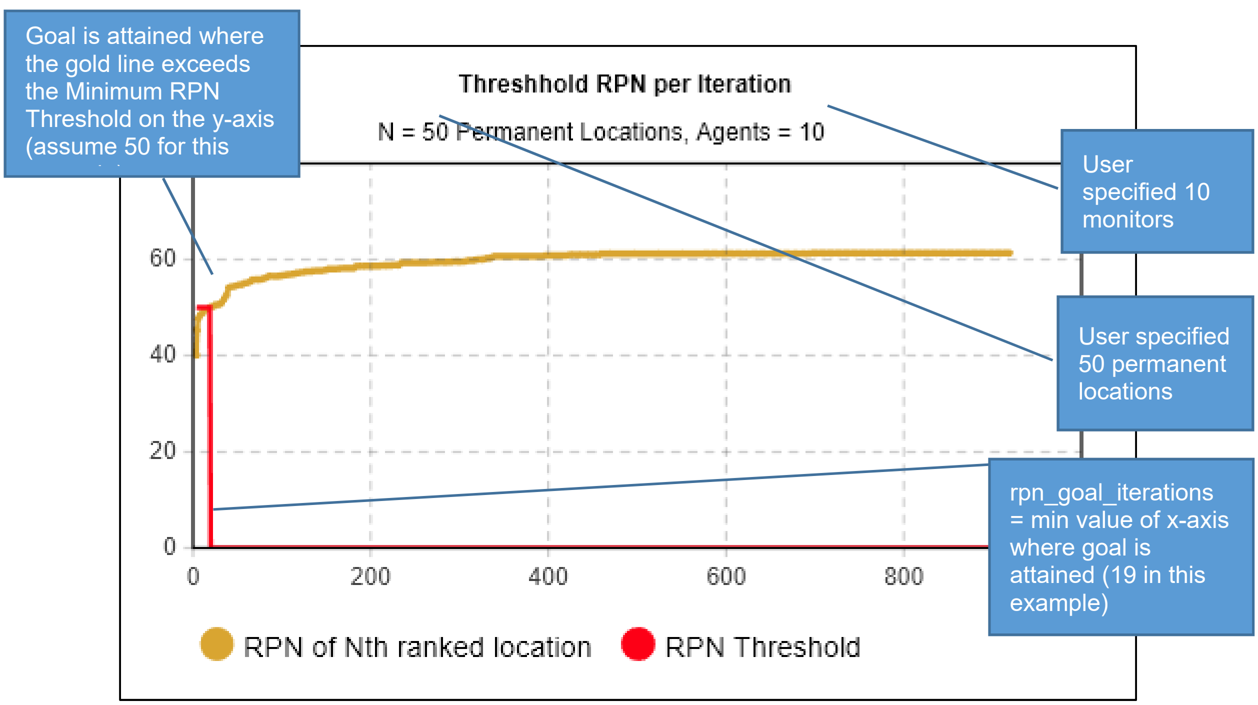
Figure 4-44: Operations of the greedy algorithm

4.6.11 Simulation output

As discussed previously, the objective function is to minimize the cost of finding a specified number of locations that exceed a specified risk threshold. The simulation labelled "N" as the parameter for the specified number of locations which is also referred to as the number of continuous monitor locations, or "permanent locations". Consequently, the output of the simulation displays and stores the N^{th} RPN at each iteration as well as a plot of the N highest RPNs.

The simulation gives an output in terms of a time series chart depicting the N^{th} ranked RPN along with performance metrics, as shown in figure (4-45) where the x-axis is the iteration count and the y-axis is the RPN of the N^{th} ranked location. In the example shown in the figure, there are 10 agents (sensors) searching for 50 locations (N) with RPN values greater than or equal to 50 (Minimum RPN threshold). There were 19 iterations required to meet this condition at a cost of $56,400. In the chart shown in figure (4-44), the gold line shows the progression of the search in terms of improving the

N^th ranked RPN. In the example discussed in this chapter, five iterations of 10 monitors were required before a 50^th ranked location was available. At that point the 50^th ranked location shows an RPN of approximately 40, the first plotted point of the yellow line. As the search progressed, the 50^th ranked RPN improved significantly before leveling to minor incremental improvement. The red line illustrates the threshold RPN set at 50. Therefore, the single constraint of the search is met at the point of intersection between the red line and yellow line which is the least number of iterations satisfying the condition that the N^th ranked location is greater than or equal to the threshold RPN.



Minimum RPN Threshold: 50.0

Number of iterations to achieve minimum RPN threshold: 19.0

Cost to achieve minimum RPN threshold: 56400.0

Number of locations in excess of the minimum RPN threshold: 51.0

Figure 4-45: Simulation output

4.6.12 Calibrating the simulation

The calibration of the model was based on the data obtained from City A in the Southeastern United States. It was assumed that the observed overflows in the modeled city were from manholes with the highest RPN. This assumption has three limitations:

1. RPN includes consequence ratings whereas observed overflow data does not. This leaves open the potential that locations with high RPN may be the result of high failure consequence combined with low failure probability. In these cases, the high RPN would not be expected to predict an observed overflow in historical data because the RPN is the result of failure consequences, not likelihood.
2. Overflows are suspected to be underreported non-uniformly. The implication is that by looking only at reported overflows, the risks associated with unreported overflows is ignored.
3. Observed overflows occur after surcharge, the definition of failure in this research. It is possible that a significant number of pipes fail without the surcharge reaching the subsurface structures or the surface where they can be observed.

The procedure for calibrating the model is summarized as follows:

1. There were 133 observed overflows in the historical data. Therefore, the 133 manholes in the simulation with the highest RPNs were labelled as the locations of failure.

2. In order to calibrate spatial autocorrelation, a comparison was conducted between the simulation and the historical data for the number of hotspots and the Moran's I statistic.
3. The simulation parameters were adjusted until a reasonable match was achieved on number of hotspots and Moran's I.

4.6.12.1 Calibration of hotspot distribution

Two techniques were used to analyze hotspots, Point Kernel Density and Grid Counts.

4.6.12.1.1 Point kernel density

Overflow locations were geocoded in the modeled city's GIS database. Using the analysis tools of the GIS software it was possible to calculate the density of the overflow locations. The map of these densities is shown in figure (4-46). A visual inspection of the contours indicates 10 distinct local optima that were considered clusters.

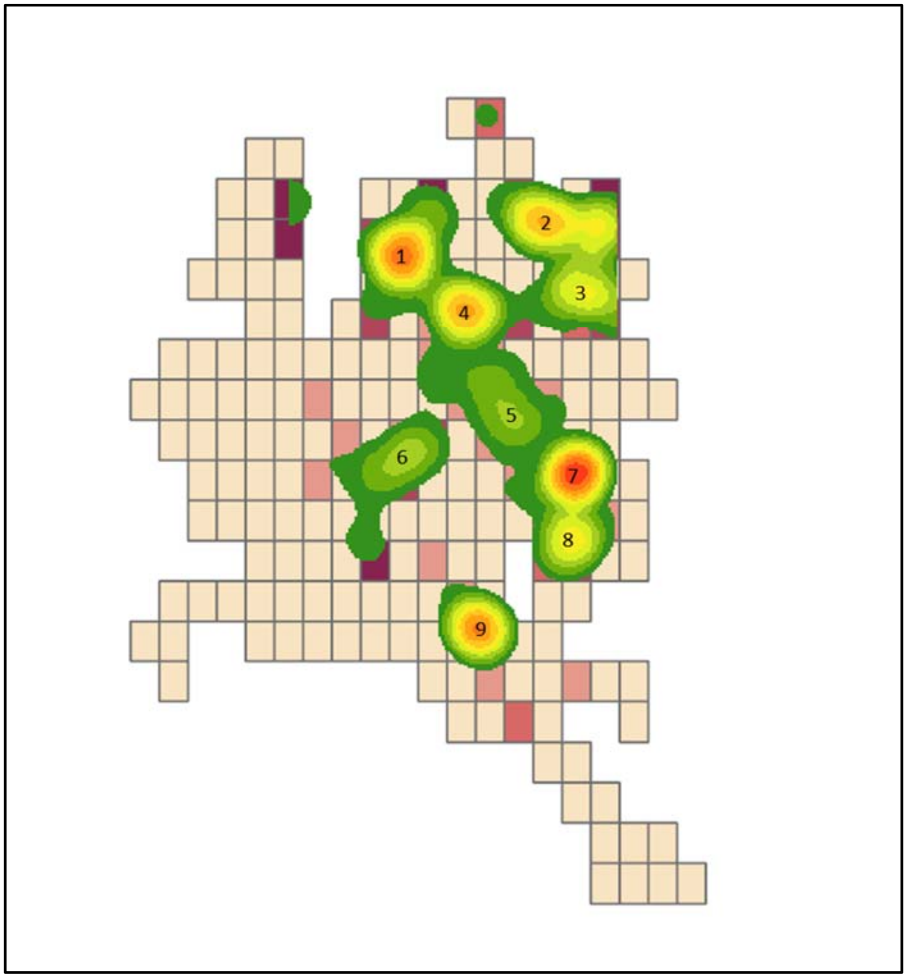


Figure 4-46: Point Kernel Density

4.6.12.1.2 Grid count

A second method was employed to identify the hotspots using the modeled city's GIS database which is a count of the observed overflows within the fishnet grid of the sewer network. The map of these densities is shown in figure (4-47). The cells are shaded based on the count of overflows, with darker shades indicating a higher count. Clusters were considered any shaded cells completely surrounded by unshaded cells. A total of nine clusters were identified using this technique.

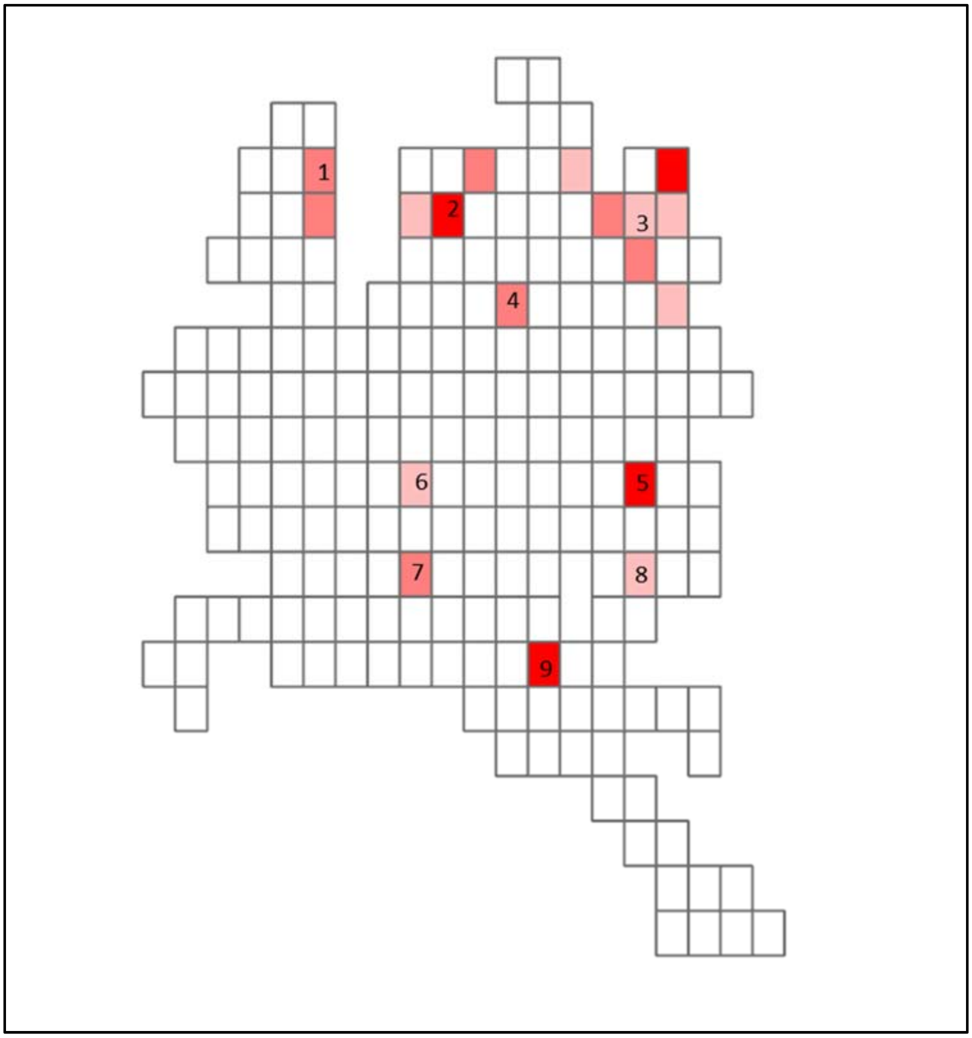


Figure 4-47: Grid Count

A comparison of the two methods shows that they both have roughly the same number of clusters centered in the same areas. It is important to remember that the goal of the calibration was not an exact match to the modeled city, but rather a realistic approximation of the distribution of risk, since risk distribution will vary between systems and over time. Therefore, in the rest of the analysis, the grid count method was used because of its computational simplicity compared to kernel densities.

4.6.12.2 Calibration results

Multiple simulation runs were conducted using various parameters of hotspots and cool spots as described previously. At each run, the output of the simulation was imported into the GIS tool where comparisons were made to the hotspot count and Moran's I statistic of the observed data. The simulation achieved a reasonable match to the observed data at the parameter settings shown in figure (4-48) below.

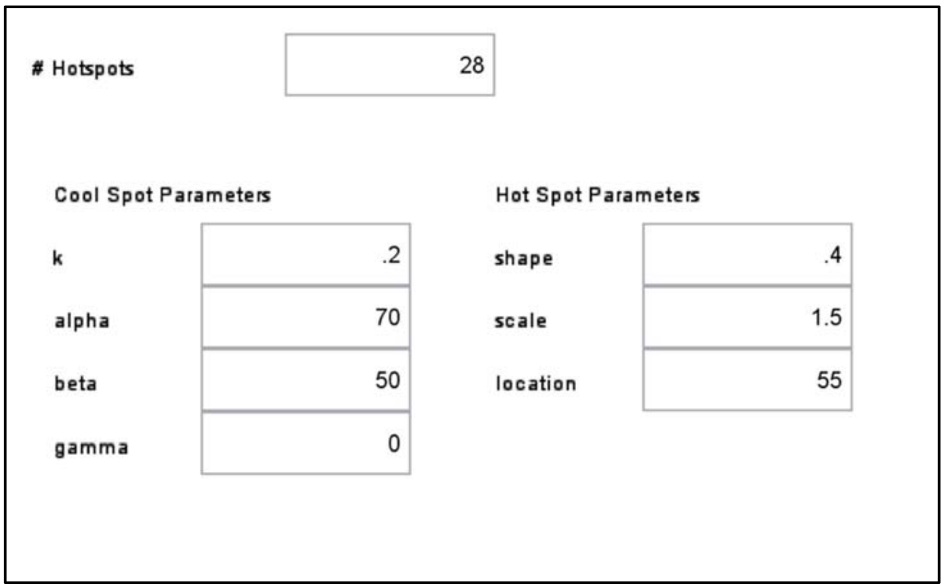


Figure 4-48: Simulation Parameter Settings

A side-by-side map of simulated versus observed hotspots is shown in figure (4-49) in which the simulated hotspots are shown on the left. As seen from the figure, there were eight hotspots in the simulation run that produced this graph compared to nine in the observed overflow data. Repeated runs of the simulation distributed hotspots in different locations and with slightly different counts but with similar realism.

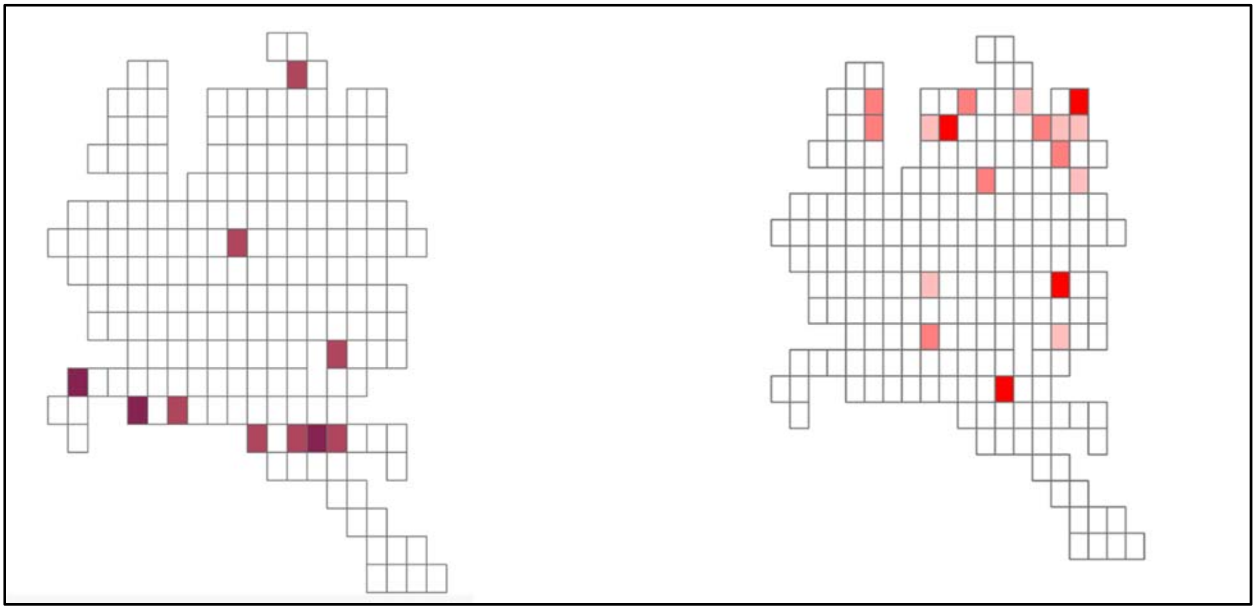


Figure 4-49: Comparison of Simulated and Observed Hotspots

The simulation also produced spatial autocorrelation metrics similar to the observed failures as shown in figure (4-50) in which the simulated values are on the left. The comparison values are the Moran's Index, the z-score, and the p-values as shown in table (4-17). The p-values between the simulation and the observed data are very similar, indicating a high probability that the observations are clustered.

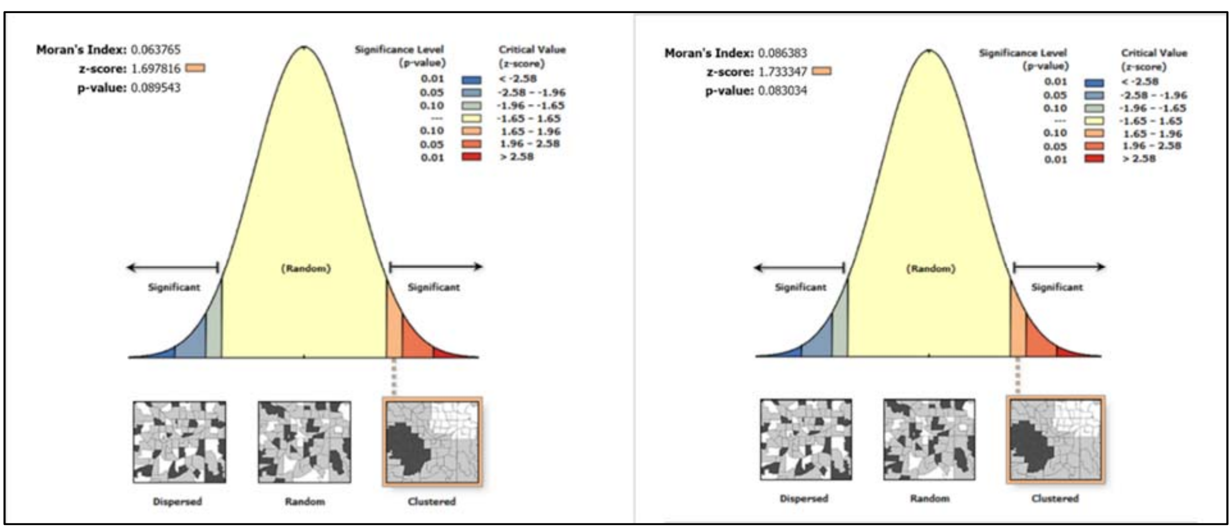


Figure 4-50: comparison of Spatial Autocorrelation Metrices

Table 4-17: Comparison between the simulated and observed data

Statistic	Simulation	Observed
Moran's Index	0.064	0.086
z-score	1.698	1.733
p-value	0.090	0.083

As a result, all screening and optimization experiments presented in this research were conducted with the parameters resulting from this calibration. However, the simulation parameters are sufficiently robust to facilitate calibration to a wide range of hot spot frequencies and spatial distributions.

4.7 Design of Experiments

Design of Experiments (DOE) was employed as the tool for evaluating results of various algorithms and parameters. In most cases, fractional factorial experiment designs were required due to the high number of factors. In screening experiments only one replicate was made for each treatment, while in optimizing experiments, three replicates were performed for each treatment in order to estimate the variability due to the intentional randomness in the simulation. For each algorithm, screening and optimization experiments were conducted to estimate the best parameters for each algorithm. Algorithms were then compared based on the mean objective function values for each algorithm for the treatments utilizing its best estimated parameters.

4.7.1 Experiment objectives

The primary objective of the experiments was to determine the algorithm and associated parameters that minimized the objective function. There are three components to this objective. The first is to determine what parameters achieve the best performance for each algorithm. The second is to select the algorithm that provides the best performance in terms of minimum cost. The third is to conduct a sensitivity analysis of the selected algorithm in order to evaluate its robustness. Based on these objectives, several questions were needed to be answered:

1. Does the neighborhood function affect the outcome?
2. Does the movement depending on RPN affect the outcome?
3. Is there an interaction with the environment parameters (e.g. hotspot and cool spot distribution)?
4. Do different risk tolerances, indicated by max number of sites to actively manage and minimum RPN threshold, lead to different sensor placement strategies?
5. Are there any impacts on the outcome if some hot spot locations are known from the outset?

4.7.2 DOE strategy

The simulation contained 58 user-controlled parameters which are listed in table (4-18) and cross referenced to the simulation initialization screen in figure (4-51). Multiple experiments were conducted for which only the primary experiment factors were varied. The experiment strategy required that some experiments contain 11 factors with two levels each, with three replicates for each treatment. This would have required 6,144 experiment runs to collect data on every combination of factors for a single experiment. This was time prohibitive, hence a fractional factorial experiment design was used as it provided a significant efficiency advantage.

Table 4-18: The simulation user-controlled parameters

Number	Simulation Parameter Name	Description
1	Algorithm	Which of 4 search algorithms
2	Alpha	Cool spot parameter
3	Beta	Cool spot parameter
4	cooling rate	Simulated annealing parameter
5	costPerIteration	Cost per level meter per iteration
6	excelFile	Input file name - defaults to manholes.xls
7	Gamma	Cool spot parameter
8	hoodSource	Either probabilistically or from shape file. Shape file option never tested.
9	isEnhanced	Enhanced simulated annealing flag
10	Kappa	Cool spot parameter
11	knownHotspots	Number of known hotspots for seeding starting locations
12	maxDistance1	Maximum radius (in feet) to move for RPN 0-10
13	maxDistance2	Maximum radius (in feet) to move for RPN 10-20
14	maxDistance3	Maximum radius (in feet) to move for RPN 20-30
15	maxDistance4	Maximum radius (in feet) to move for RPN 30-40
16	maxDistance5	Maximum radius (in feet) to move for RPN 40-50
17	maxDistance6	Maximum radius (in feet) to move for RPN 50-60
18	maxDistance7	Maximum radius (in feet) to move for RPN 60-70
19	maxDistance8	Maximum radius (in feet) to move for RPN 70-80
20	maxDistance9	Maximum radius (in feet) to move for RPN above 80
21	minRPNThresh old	The minimum threshold for active risk management
22	Mu	Hot spot location parameter
23	numHotspots	Hot spot parameter
24	numInspectors	Number of inspectors in the sequential search algorithm
25	numMonitors	Number of monitors (agents) searching for manholes
26	numNearestMa nholes1	Nearest_x for Enhanced Sim Annealing for RPN 0-10

Number	Simulation Parameter Name	Description
27	numNearestManholes2	Nearest_x for Enhanced Sim Annealing for RPN 10-20
28	numNearestManholes3	Nearest_x for Enhanced Sim Annealing for RPN 20-30
29	numNearestManholes4	Nearest_x for Enhanced Sim Annealing for RPN 30-40
30	numNearestManholes5	Nearest_x for Enhanced Sim Annealing for RPN 40-50
31	numNearestManholes6	Nearest_x for Enhanced Sim Annealing for RPN 50-60
32	numNearestManholes7	Nearest_x for Enhanced Sim Annealing for RPN 60-70
33	numNearestManholes8	Nearest_x for Enhanced Sim Annealing for RPN 70-80
34	numNearestManholes9	Nearest_x for Enhanced Sim Annealing for RPN above 80
35	numPermanent Locations	Number of locations being searched for in excess of minRPNThreshold
36	radius:0.25	Selection of zoom level for map
37	rangeType1	Neighborhoods or manhole search range for RPN 0-10
38	rangeType2	Neighborhoods or manhole search range for RPN 10-20
39	rangeType3	Neighborhoods or manhole search range for RPN 20-30
40	rangeType4	Neighborhoods or manhole search range for RPN 30-40
41	rangeType5	Neighborhoods or manhole search range for RPN 40-50
42	rangeType6	Neighborhoods or manhole search range for RPN 50-60
43	rangeType7	Neighborhoods or manhole search range for RPN 60-70
44	rangeType8	Neighborhoods or manhole search range for RPN 70-80
45	rangeType9	Neighborhoods or manhole search range for RPN above 80
46	rangeValue1	Max neighborhoods or manholes (see rangeType) for RPN 0-10
47	rangeValue2	Max neighborhoods or manholes (see rangeType) for RPN 10-20
48	rangeValue3	Max neighborhoods or manholes (see rangeType) for RPN 20-30

Number	Simulation Parameter Name	Description
49	rangeValue4	Max neighborhoods or manholes (see rangeType) for RPN 30-40
50	rangeValue5	Max neighborhoods or manholes (see rangeType) for RPN 40-50
51	rangeValue6	Max neighborhoods or manholes (see rangeType) for RPN 50-60
52	rangeValue7	Max neighborhoods or manholes (see rangeType) for RPN 60-70
53	rangeValue8	Max neighborhoods or manholes (see rangeType) for RPN 70-80
54	rangeValue9	Max neighborhoods or manholes (see rangeType) for RPN above 80
55	scaleX	Hot spot parameter
56	sensorRange	Number of manholes that a sensor must be away from previously monitored manhole
57	sequentialFile	Excel file containing corrections to manhole connectivity problems.
58	shapeX	Hot spot parameter

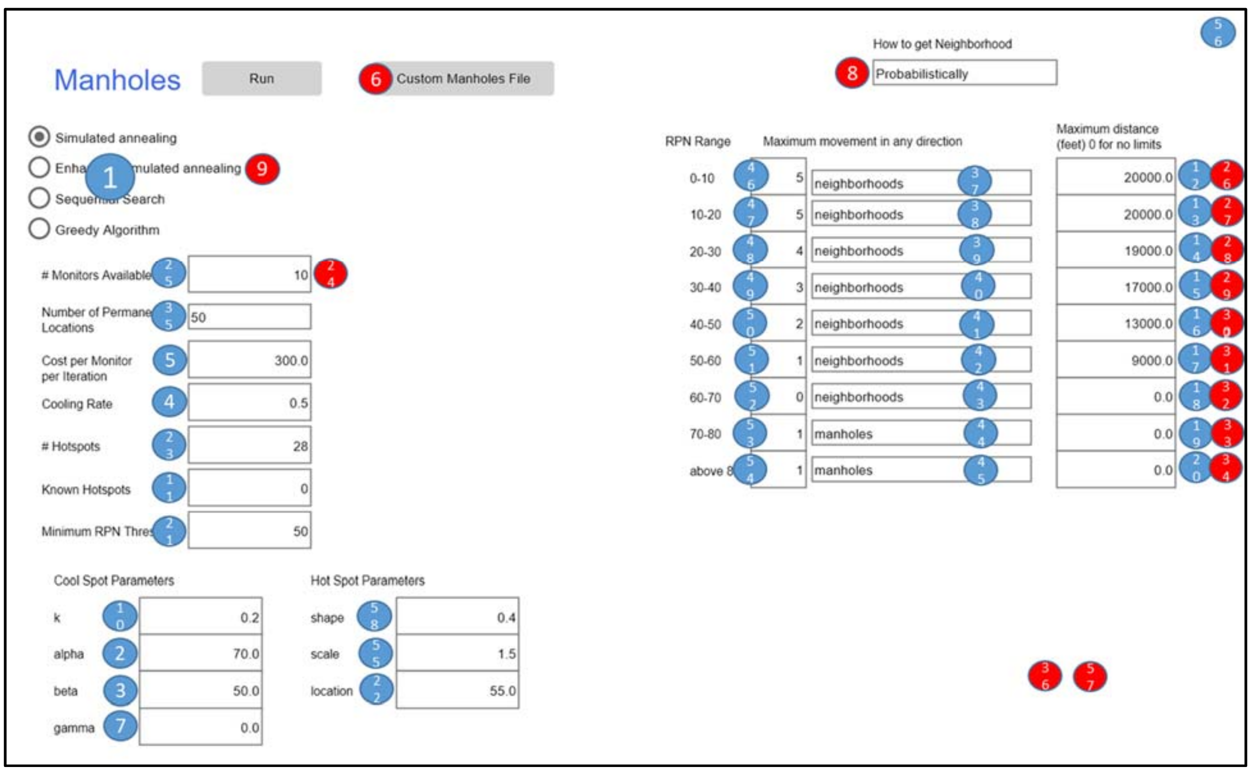


Figure 4-51: Simulation initialization screen

The available parameters were treated in four distinct ways in order for the experiment to efficiently meet the objective. These distinctions are described below and summarized in table (4-19).

1. Each algorithm was optimized independently. Since the available parameters differed for each algorithm, the experiment strategy was to optimize parameters for each algorithm individually before comparison. Early trials using “algorithm” as a factor ran into issues due to the dissimilar parameters in each algorithm and the added complexity of adding factors and levels.
2. Primary experiment factors. These were the parameters of greatest interest to study in the optimization of each algorithm. There were 11 parameters for the two simulated annealing algorithms and fewer parameters the other two algorithms.
3. Sensitivity factors. There were 13 parameters outside of the primary experiment factors that were of interest in this study after the primary experiment factors were optimized. These parameters are:
    a. Eight related to the distribution of hot spots and cool spots. The purpose of experimentation with these parameters was to assess the robustness of the optimized algorithm on a variety of sewer system environments.
    b. The parameter knownHotSpots was included to test a hypothesis that sensors should be placed in locations where failures historically occurred.

c. The parameter costPerIteration was included to quantify the cost differences between sequential search and simulated annealing. Sequential search is often used in inspection programs. Therefore, the magnitude of cost savings is an important argument to use in favor of employing a metaheuristic.
d. The parameter minRPNthreshold was included to test the sensitivity of the optimum parameters to varying risk tolerances. One hypothesis is that the jump function is related to the minRPNthreshold choice.
e. The parameter numPermanentLocations was included primarily to quantify the additional risk mitigation possible with increased resources to continuous monitoring and estimate the marginal benefit of additional spending.
f. The parameter sensorRange was included to quantify the benefit of technological improvements in sensing technology.

Table 4-19: Ways of treating the available parameters

Experiment Purpose	Variable (companion variable)	Number of factors in Based Simulated Annealing	Number of factors in Enhanced Simulated Annealing
Optimize one at a time	Algorithm (Enhanced)	Not varied within experiment runs	
Primary experiment factors	Cooling rate	1	1
	maxDistance 1-9 or rangeValue 1-9 (rangeType 1-9)	9	
	numNearestManhole 1-9		9
	numMonitors (numInspectors)	1	1
Sensitivity factors	costPerIteration, alpha, beta, gamma, kappa, knownHotspots, minRPNthreshold, mu, numHotspots, numPermenantLocations, scaleX, sensorRange, shapeX	Not varied within experiment runs	
Maintenance Variables	excelFile, hoodSource, radius, sequentialFile	Not Applicable	

Note that in the above table "companion variables" were included. These are parameters that are used in conjunction with other parameters in a paired fashion, however only one of them only will be populated in an experiment. For example, numMonitors and numInspectors are parameters for the number of agents in the simulated annealing and sequential search algorithms, respectively. Another example is rangeValue and rangeType which are used together to designate a jump magnitude such as "4 manholes" or "2 neighborhoods".

4.7.3 Treatment selection

4.7.3.1 Method for selecting parameters

In order to select the parameters, experiments were conducted in three phases - screening, optimization, and sensitivity. The first two were performed for each algorithm. Screening experiments were fractional factorial designs for the purpose of eliminating non-significant factors and gaining an approximate understanding of where the good parameter values existed. At the same time, the optimization experiments were conducted to explore in more detail the regions of interest indicated by the screening experiment results. Iterations of optimization experiments continued until either a parameter reached a limit, or an optimum parameter value was revealed by curvature in the response variable. Special experiments were designed to test the sensitivity by employing the sensitivity factors. Following is a description of the primary experiment values:

1. Cooling rate. This parameter applies only to the base simulated annealing and enhanced simulated annealing. The cooling rate specifies the steps at which the simulated annealing temperature is reduced at each iteration. High cooling rates produce faster search convergence but lower the resolution of the results.
2. Max distance 1-9. This parameter applies only to the base simulated annealing and greedy search. It is a table of values that indicates the maximum distance, in feet, that an agent may move in a single iteration. Each of the nine values in the table corresponds to the RPN of the current location in increments of 10. Max distance 1 applies to RPN between 0-10, Max distance 2 to RPN between 10-20, etc.
3. Range value 1-9 and range type 1-9. This parameter applies only to the base simulated annealing and greedy search. It is an alternative move designation to Max distance that allows movement to be designated as a number of manholes or a number of neighborhoods away. Moreover, range values may be used in conjunction with Max distance. For example,

moves for RPN values of 0-10 may be specified as a distance in feet in the same simulation where moves for RPN values of 10-20 are specified as a number of manholes away.

4. Number of nearest manholes 1-9. This parameter applies to the enhanced simulated annealing only. It is a table of values specifying the number of nearest manholes within the neighborhood of an agent corresponding to RPN values in increments of 10. Agents are restricted to movements only within these defined neighborhoods.
5. Number of monitors/number of inspectors. This parameter applies to all algorithms and it designates the number of agents active during the search.

4.7.3.2 Choice of factor levels

For the screening experiments, factor levels were chosen to be very broad, guided by the authors experience in sewer system monitoring. Table (4-20) is a list of the primary experiment variables with their low and high levels for screening experiments and the rationale for selecting those levels.

Table 4-20: Primary experiment variables for the screening experiments

Parameter	Low Level	High Level	Rationale
Cooling rate	1	20	Preliminary screening experiments indicated slow convergence at values below 1 and frequent early termination at values above 20.
Max distance	1,000	30,000	1,000 feet is the approximate sensor range. 30,000 feet

Parameter	Low Level	High Level	Rationale
			is the approximate distance between observed hot spots.
Range value + type	3 manholes	3 neighborhoods	3 manholes is the estimated sensing range of a monitor. 3 neighborhoods were the maximum distance between observed overflows.
Number of nearest manholes	3	1,000	3 manholes are within sensing range of each other. 1,000 manholes covered the approximate distance between hot spots.
Number of monitors/inspectors	10	150	Experience in pilot program was that 10 was too few to achieve scale of operations. Above 100 produced expensive “over solutions”.

For each experiment, several factors were held at a constant level as shown in table (4-21).

Table 4-21: Values and rationale for constant factors

Parameter	Value	Rationale
Cost per iteration	300	Published price for 1 month of level monitoring, including installation
Cost per inspection	470	CCTV cost from EPA Report to Congress (US EPA 2004a)
Cool spot shape – alpha	70	Calibration of 4-parameter Dagum distribution to hypothesized RPN
Cool spot scale – beta	50	
Cool spot shape – kappa	0.2	
Cool spot location – gamma	0	
Known hotspots	0	Base case assumes no prior knowledge of hotspots

Parameter	Value	Rationale
Minimum RPN threshold	50	The bin containing the 90th percentile of RPNs
Number of hotspots	28	Calibration of hotspots to hypothesized RPN
Number of permanent locations	50	Author's experience of a modest monitoring program
Hot spot location - mu	55	Calibration of 3-parameter General Extreme Value distribution to hypothesized RPNs
Hot spot scale - sigma	1.5	
Hot spot shape - kappa	0.4	
Sensor range	0	Allow the smallest movement possible

4.7.3.3 Response variable

The response variable in all experiments was the minimum total cost that satisfied the single constraint. The simulation updates the total cost at the end of each iteration and displays the minimum cost that meets the constraint.

4.7.3.4 Cost per iteration/ cost per Inspection

Cost per iteration and cost per inspection were treated as sensitivity factors in the experiments because they will differ between sewer system owners. It is conceivable that unit cost differences between monitoring and inspection could lead to a change in optimizing behaviors. The default value of $300 for cost per iteration was based on 2018 prices from an industry-known technical services provider of flow monitoring data. Municipalities pay a $300 flat rate and receive 30-days of level data in csv format, which is suitable for calculating risk occurrence ratings. The service provider provides all installation, maintenance, and data collection associated with collecting this data. At the same time, the default value of $470 for cost per inspection is based on cost and productivity assumptions for closed-circuit television inspection (CCTV). The formula used to estimate the cost per inspection was:

Average cost per linear foot in 2002 * 2002-2018 inflation factor * average feet between manholes

The average cost per linear foot is based upon a 12-city survey published in the 2004 EPA Report to Congress (US EPA 2004a). Although the data is quite old, it was accepted as the best data available due to its unbiased source and its representation of different regions of the country. The variation is pricing between cities is notable, ranging from $0.27/foot in Santa Rosa, CA to $1.63/foot in Sacramento less than 100 miles away. This reflects not only differences in job complexity and local pricing, but also the way in which utilities calculate their cost of inspection.

An estimate of average feet between manholes was required to determine the price equivalent to monitoring a pipe segment with a level monitor. A report produced by Black & Veatch for The American Society of Civil Engineers (ASCE) and the U.S. EPA reported that average manhole spacing is 236 feet (Nelson, Habbian, and Andrews 2000). This allowed the final calculation of $470 per inspection ($1.99 per foot & 236 feet).

4.7.3.5 Cost equivalence of monitoring and inspection

The technical service provider who supplied the unit cost also provided the productivity assumptions which indicated that a single level monitor was capable of providing level data for two manholes upstream and downstream of its installed location. Therefore, using the average distance of 236 ft between manholes results in a single monitor collecting performance data over a length of 944 feet per installation. In addition, the installation duration required for the methodology proposed in this research is 30 days.

The same technical service provider was the source for the productivity assumption of 1,200 feet per day per inspection team for CCTV. Consequently, over a

4-week month, 20 workdays, this team would inspect 24,000 feet at a cost of $1.99 per foot, or $47,760. For the same $47,760 spent on inspections in a month, 159 level meters could be installed for a month (47,760/300). These meters would collect data over an effective distance of 150,100 feet which is more than six times the area inspected at the same price using CCTV.

As seen, this is a strong argument in favor of monitoring as it provides data sufficient for risk occurrence rating at a much lower cost per foot than CCTV inspection. In addition to this advantage, the monitoring data is continuous over the 30 days unlike the CCTV data which is a literal snapshot of the visible physical condition of the pipe.

4.7.4 Experiment phases and design decisions

The experiment design specifications are outlined in table (4-22). The BSA was divided into separate experiments to compare different neighborhood functions, one using a distance in feet to determine neighbors where agent movement was allowed (BSA – Dist), the other using the number of neighborhoods away based on defining neighborhoods as locations sharing common characteristics believed to influence failure probability (BSA – Hood).

Table 4-22: Results of experiment design

Algorithm	Phase	Fact.s	Lev.s	Res.	Fract.	Repl.	Ctr Points	Axial Points	# of Runs
ESA	Screen	11	2	V	1/64	3	3	0	99
ESA	Optimize	2	2	CCD	Full	3	15	12	39
BSA – HOOD	Screen	11	2	IV	1/64	3	3	0	99
BSA – HOOD	Optimize	4	2	CCD	Full	3	21	24	93
BSA – DIST	Screen	11	2	IV	1/64	3	3	0	99
BSA – DIST	Optimize	6	2	CCD	1/2	3	30	42	264
SS	Optimize	1	15	Full	Full	3	0	0	45

Algorithm	Phase	Fact.s	Lev.s	Res.	Fract.	Repl.	Ctr Points	Axial Points	# of Runs
Greedy	Screen	1	12	Full	Full	3	0	0	36
Greedy	Optimize	1	4	Full	Full	7	0	0	28

Results of the screening experiments determined the selection of factors for the optimization experiments. In several instances, excursion experiments along the path of steepest descent were conducted to add resolution to the shape of the solution space.

4.7.4.1 Number of factors

4.7.4.1.1 Screening phase

The purpose of screening was to determine which factors have significant effects on the total cost in terms of practical and statistical significance. It was assumed that the 3-way and higher interactions were not significant and that confounding main effects with 3-way interactions was unlikely to be significant. Likewise, the efficiency of 1/64th fraction experiment designs was an acceptable risk for allowing some 2-way interactions to be confounded. As the experiments were conducted, it was necessary to explore 2-way confounding.

Simulated annealing simulations, both BSA and ESA, contained 11 primary factors: the nine RPN-based movement magnitude values, the cooling rate, and the number of agents. The Greedy algorithm contained only 1 primary factor, the number of agents. The remaining factors in the Greedy algorithm experiments were held at the BSA-DIST optimums to allow direct comparison. Sequential search did not have a screening phase due to the fact that only one factor was needed in the experiment, which was the number of inspectors.

4.7.4.1.2 Optimization phase

The number of factors for optimization experiments depended on the number of significant factors identified in the screening phase. For example, in the ESA algorithm, only 2 of the 11 primary factors were required to characterize the changes in the response variable.

4.7.4.2 Factor levels and midpoints

For screening experiments using some form of the simulated annealing algorithm a 2^k fractional factorial experiment was used. This required two levels of each factor. To avoid any issues with varying units used for the factors, coded units of -1, 0, and 1 were used in the statistical analysis for the low values, midpoints, and high values respectively. Experiments involving the Greedy algorithm and Sequential Search involved a single factor therefore it was practical to conduct full-fraction experiments with multiple levels.

Optimization experiments involving the simulated annealing algorithms began with Central Composite Design experiments. The motivation for this design was to reveal any curvature, which would indicate a possible local optimum. Factor levels and midpoints were dependent upon the screening experiment results along with excursion experiments along the path of steepest descent.

4.7.4.2.1 Resolution and fraction

Screening experiments involving simulated annealing were resolution IV which allows the conclusions to be drawn with relatively few experimental runs. The choice for resolution IV was made based on the belief that 3-way interactions were insignificant and that 2-way interactions, if significant, could be deconvoluted based on knowledge of the search algorithm operations. This choice accepts the risk of confounding main effects with 3-way interactions and confounding some 2-way interactions with other 2-way interactions. The selection of the fraction was driven by the requirement to maintain resolution IV along with the desire to conduct no more than 100 simulation runs per experiment.

4.7.4.2.2 Replications

For each treatment, three replications were performed to examine the effects of the stochastic elements in the simulation, which included random initial placement of agents, random placement of hot spots, and randomness in the distribution of RPNs within hot and cool spots. The value of 3 replications was proven to be sufficient in most experiments as shown by tests of statistical significance in the factors. In some cases, supplemental replications were added for verification. For example, in the final comparison of the simulated annealing algorithms, ten replications were performed.

4.7.4.2.3 Center points

All two-level experiments including at least 3 replications of center point runs. This allowed curvature in the response surface to be detected. The presence of curvature indicated that factor levels may be near a minimum or maximum level. Experiments with more than 2 levels contained sufficient data to test for curvature.

4.7.4.3 Stopping criteria

The experiments were considered to have met their objectives when the values of the factors reached a minimum, maximum, or inflection. For example, if the response value achieved its optimum when the number of agents = 1, then no further reduction of agents was sensible as a minimum factor level was reached. An example of an inflection is shown in the right pane of figure (4-52). The mean value of the objective function was achieved when the number of monitors factor was at its middle level, 2. Movement in either direction resulted in the worsening of the objective function. Thus, the experiment was concluded.

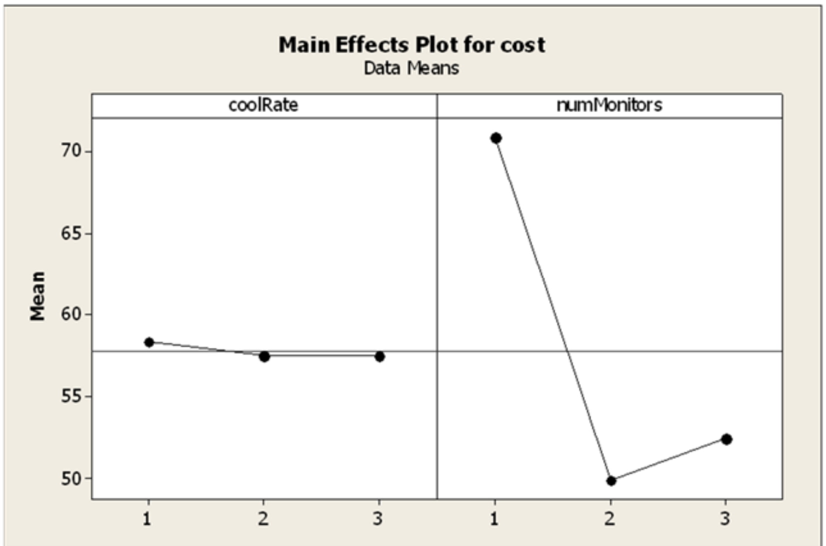


Figure 4-52: Inflection stopping criteria

4.7.4.4 Sensitivity

4.7.4.4.1 Cost per iteration

The purpose of exploring cost per iteration is to establish an economic comparison of the best performing metaheuristic search algorithm versus sequential search. The output of this experimentation is cost per iteration that would be required to achieve the same result as that of continuous monitoring using the optimized simulated annealing movement strategy.

4.7.4.4.2 Hotspot and coolspot parameters

The simulation contained seven parameters that determine the number of hotspots and the distribution of RPN's within hotspots and cool spots which are represented by the variables numHotSpots, alpha, beta, kappa, mu, scaleX, and shapeX. Note the gamma parameter was held at zero to calibrate RPN values >= 0. A two-level, 1/8th fractional factorial experiment was designed using the optimal search algorithm and fixed values for all other parameters. Three center points were added. This required a total of 51 experimental runs.

4.7.4.4.3 Risk profile parameters

The risk profile can be characterized by the number of permanent locations desired to be found that meet the minimum RPN threshold which are represented by two parameters: numPermanentLocations and minRPNthreshold. Low minRPNthreshold and high numPermanentLocations indicate a low tolerance for risk. On the other hand, high minRPNthreshold and low numPermanentLocations indicate a high tolerance for risk. A 2-factor, 4-level, 3-replicate full factorial experiment was designed to quantify the change in the cost objective to varying degrees of risk threshold. This required 48 simulation runs.

OPTIMIZATION & IMPLEMENTATION

5.1 Optimization of the simulated annealing algorithm parameters

In order to apply the simulation model developed in the previous chapter and obtain results for manhole selections, experimentation was performed on each of the three variants of the simulated annealing search algorithm. The first variant utilized a neighborhood function which categorized neighbors based solely on their distance, in feet, from the agents' starting location. This variant is labelled "BSA Dist" for "basic simulated annealing – distance". The second variant defined neighbors based on the shared characteristics hypothesized to be predictive of failures. Neighbors were categorized based on the number of adjacent neighborhoods away from the agent or the number of manholes away located on the same pipe. This variant is labelled "BSA Hood" for "basic simulated annealing – neighborhood". The third and last variant utilized the knowledge gained in assessing the risk severity. It categorized the neighbors based on the closest manholes with a risk severity rating close to that of the starting location. This variant is labelled "ESA" for enhanced simulated annealing. The results of this battery of experiments will be shown for all three variants at each stage of the experimentation process in order to highlight their differences.

5.1.1 Screening experiments: main effects model

For the screening phase, resolution IV fractional factorial designs were employed. In total, there were 11 factors. The search cost was used as the response variable. Factors were considered to be statistically significant if their p-values were less than or equal to 0.05, i.e. a 95% confidence level. The following table (5-1) summarizes the significant factors that were employed and the summary statistics for each of the three algorithms at the conclusion of the screening phase.

Table 5-1: Summary statistics for the screening phase algorithms and the significant factors employed

Algorithm	Significant Parameters	R-Sq statistic	Lack of Fit assessment	Curvature assessment	Model sufficient
BSA Dist	numMonitors coolingRate rangeValue3 rangeValue5 rangeValue6	39.55%	p-value of 0.00 indicated missing factors or interactions	p-value of 0.597 indicated insignificant curvature	No
BSA Hood	numMonitors coolingRate rangeValue5 rangeValue7	47.56%	p-value of 0.00 indicated missing factors or interactions	p-value of 0.286 indicated insignificant curvature	No
ESA	numMonitors numNearMH6	33.93%	p-value of 0.00 indicated missing factors or interactions	p-value of 0.094 indicated insignificant curvature	No

The 11 factors represent the following:

1. numMonitors is the number of monitors involved in the search, where each monitor is represented by an agent in the simulation.
2. coolingRate is the simulated annealing parameter that determines the rate at which the temperature variable falls, which directly influences the probability of accepting moves to inferior solutions.
3. The three rangeValue parameters for the BSA Dist. algorithm are maximum distances, in feet, that agents may move in any iteration.
4. The two rangeValue parameters for the BSA Hood algorithm are maximum number of manholes or neighborhoods that agents may move in any iteration.
5. numNearMH6 for the ESA algorithm is the number of closest locations that agents may move to an any iteration.

5.1.2 Screening experiments – 2-way interactions model

Because the lack of fit was significant in all of the main effects models, the experimental data was fitted with models that included all statistically significant 2-way interactions. The results of this fitting are shown in table (5-2).

Table 5-2: Results of 2-way interaction models

Alg.	Parameters with Significant Effects	R-Sq	Lack of Fit	Curv.	Model sufficient
BSA Dist	numMonitors coolingRate rangeValue2 rangeValue3 rangeValue5 rangeValue6 numMonitors*coolingRate numMonitors*rangeValue1 numMonitors*rangeValue2 numMonitors*rangeValue5 numMonitors*rangeValue6 coolingRate*rangeValue2 rangeValue1*rangeValue3	68.58%	Lack of fit was insignificant (p-value less than 0.05)	p-value of 0.487 indicated insignificant curvature	Yes
BSA Hood	numMonitors coolingRate rangeValue5 rangeValue7 coolingRate*rangeValue5 coolingRate*rangeValue7 coolingRate*numMonitors	89.06%	Lack of fit was insignificant (p-value less than 0.05)	Curvature was significant with p-value 0.023	Yes
ESA	numMonitors numNearMH6 numMonitors*numNearMH6	52.48%	Lack of fit was insignificant (p-value less than 0.05)	Curvature was significant with p-value 0.05	Yes

5.1.3 Screening experiments path of steepest descent

Using the three 2-way interaction models, the path of steepest descent was calculated based on the coefficients of the regression models. Due to the interactions in the model, a linear programming application was used to determine the main effects settings that will minimize the response variable. The factor with the highest coefficient in absolute value was chosen as the variable to be changed manually. The other variables were proportionally modified based on the ratio of their coefficients to the manually changed factor coefficient (Montgomery 2013). Furthermore, at each step, three replications of the simulation runs were performed, and the resulting costs were averaged. This process continued until a local minimum in the response variable was discovered.

In several cases, the step sizes were modified due to the constraints on the factor levels. For instance, numMonitors could not be less than 1. Thus, in such cases, the values of the factors were estimated by the experimenter. Figure (5-1) below summarizes the results of this sequential experimentation by depicting the sequence of steps and the response variable for each algorithm.

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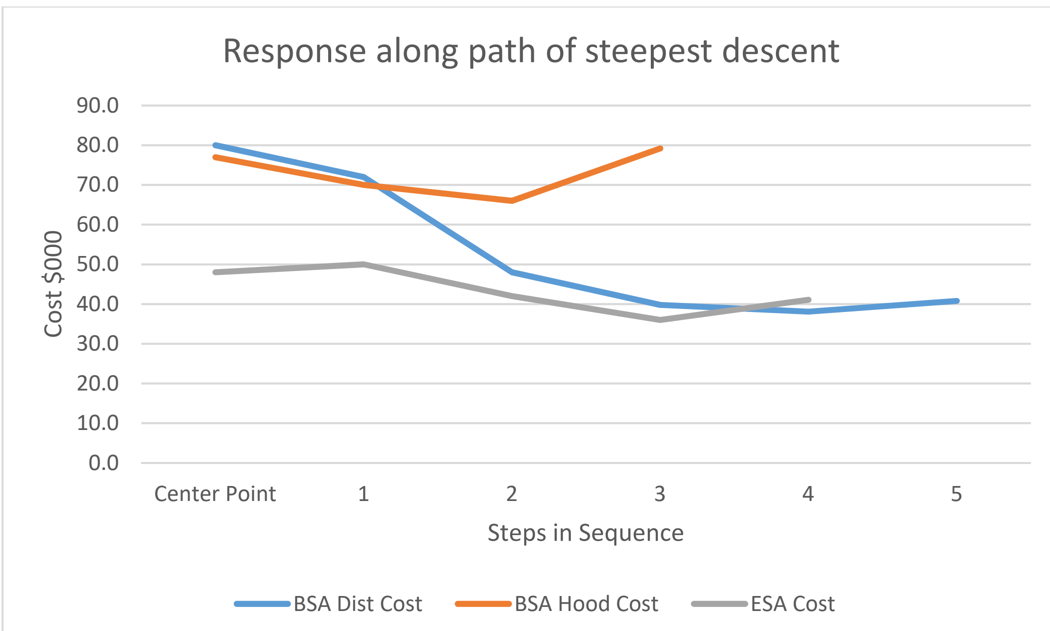

Figure 5-1: Results of sequential experimentation

As seen from the above figure, each algorithm reached a local minimum at a different number of steps from its center point. To compare the models together, the factor “numMonitors” was used as it was significant in every model. Consequently, at the stopping point of the descent, the numMonitors factors were equal to 1, 12, and 10 for BSA Dist, BSA Hood, and ESA, respectively, which are all less than their center points.

5.1.4 Optimization experiments

Optimization experiments were conducted of the stopping points of the steepest descent sequence. These experiments were Central Composite Design experiments with high and low factor settings determined by the experimenter's judgement based on experience with the simulation. At the same time, the factors that were ignored as a result of the screening experiment's results, were held at their midpoint values during optimization runs. A comparison of the results of the optimization experiments is shown in table (5-3).

Table 5-3: Comparison of the optimization experiments results

Algorithm	**Parameters with significant effects**	**R-sq statistic**	**Assessment**
BSA Dist	rangeValue5 rangeValue6 numMonitors*numMonitors rangeValue6*rangeValue6 rangeValue1*rangeValue3	19.65%	Poor model i.e. needs further validation.
BSA Hood	No statistically significant effects	Near 0%	Poor model. Factors were not varied enough to induce a significant response i.e. needs further validation.
ESA	numMonitors (p=0.071) numNearMH6	28.85%	Poor model but potentially useful.

5.1.5 Excursions

The first round of the optimization experiments produced inconclusive results. Additional simulation runs were designed and conducted for each of the three simulated annealing algorithms. The design of this round of simulations was customized to each algorithm, based on the observations in the filtering experiments and the experiments along the path of steepest descent.

5.1.5.1 BSA-Dist algorithm excursion runs

It was observed during the steepest ascent simulation runs that the response variable was sensitive to the changes in the numMonitors parameter. Based on this observation, a new set of simulations was run at the lowest possible value for numMonitors while all other factors were held at the levels implied by the optimization experiment statistical models. The results of these three simulation runs are shown in the third column of table (5-4) while the second column shows the optimal settings from the optimization experiment results, a central composite design experiment.

Table 5-4: Results of the BSA-Dist experiments at center points and minimum values

Replicate	**11 monitors, 0.1 cooling, 15k below RV6, 500 at and above RV6 as implied by CCD**	**1 monitor, 0.1 cooling, 15k below RV6, 500 at and above RV6**
Run 1	31.8	23.4
Run 2	39.6	35.1
Run 3	42.6	18.9
Average	38.0	25.8

Based on these results, a full factorial DOE was performed at the lowest range of the numMonitors parameter, these were settings of numMonitors = 1,2, and 3. The objective of this experiment was to verify the sensitivity of the response variable to the small movements around the 1-monitor simulation. The main conclusion from the results of this excursion was that: a) the fewer the monitors the better, and, b) the smaller the movement in the critical bin and above the better, with the exception that anything smaller than 500 feet restricted the agent from finding sufficient qualified locations. When this occurred, agents became trapped in suboptimal locations. Therefore, 500 feet was set as the minimum movement value.

As a final excursion, for the most influential experiment factor, numMonitors, a series of simulation runs was conducted by ranging the numMonitors from 1 to 100 in steps of 10. These results formed the basis of the final observations of the optimal parameters for the BSA-Dist algorithm.

5.1.5.2 BSA-Hood algorithm excursion runs

The results of the optimization experiments with the BSA-Hood algorithm showed that error dominated the effect from the changes in the experiment factors. The r^2 statistic was 0.00%. There were three possible explanations as to why these factors were significant in the screening experiment (r^2 = 88%) but not in the optimization experiment:

1. Missing terms in this area of the solution space. This is not likely since these terms explained so much variance in the screening experiment.
2. Insufficient replications to dampen the noise. This is one possible solution to the above problem.
3. The factors were not varied enough to induce a statistically significant response. This is likely the root cause of the problem because of the variation built into the simulation.

Based on the above, a multi-level factorial experiment was designed with five levels of the significant factors in the screening experiment, numMonitors and coolingRate. The range of variation in the factor levels was set to overlap with the screening experiment where statistically significant results were observed. The resulting model from this experiment produced a r^2 statistic of 66%, which was considered acceptable.

In addition, the results of the multi-level factorial experiment suggested best responses when the numMonitors were less than 38. A central composite design experiment was conducted in this range and the interaction plot from this experiment is shown in figure (5-2). From the interaction plot, it is obvious that there was significant curvature and interactions. Therefore, a custom Central Composite Design experiment was conducted using the midpoints noted in table (5-4).

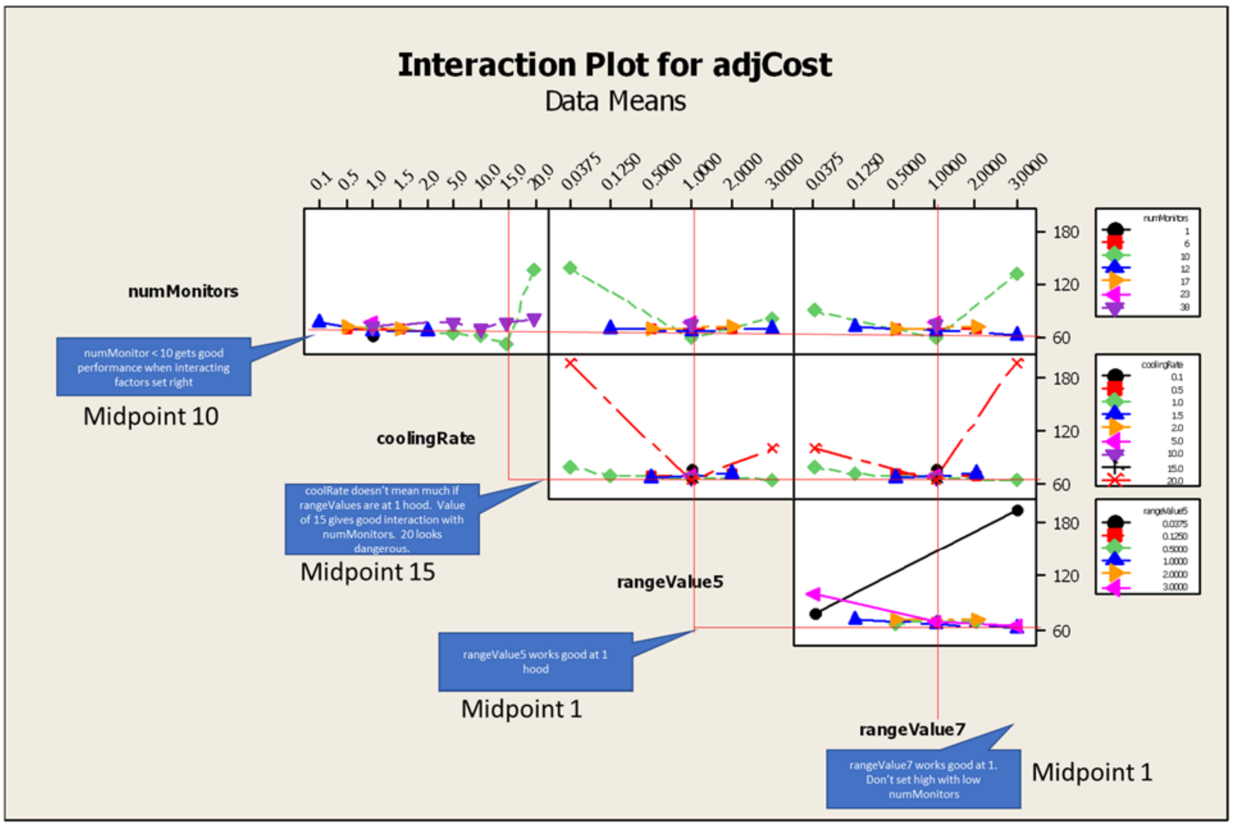

Figure 5-2: The interaction plot

A custom experiment design was selected to accommodate limitations encountered in the simulation. Due to memory requirements, the simulation could accommodate a maximum total manhole movement of around 100. Also, the simulation would not terminate with a single monitor and cooling rates above 12. The practical minimum combination was numMonitors = 5 and coolingRate = 12. After examining the final results, these limitations in the simulation did not affect the outcome of the research. The results from the custom CCD model were statistically significant, with an r^2 statistic of 77%. This model was the basis for determining optimal parameter settings for the BSA-Hood algorithm.

5.1.5.3 ESA algorithm excursion runs

The optimization experiment for the ESA algorithm yielded an r^2 statistic of 28.85%, which was judged insufficient but potentially valuable in guiding the next round of experimentation. The contour plots from the optimization experiment indicated a local minimum within an interaction of the numNearMH6 parameter and the numMonitors parameter as shown in figure (5-3).

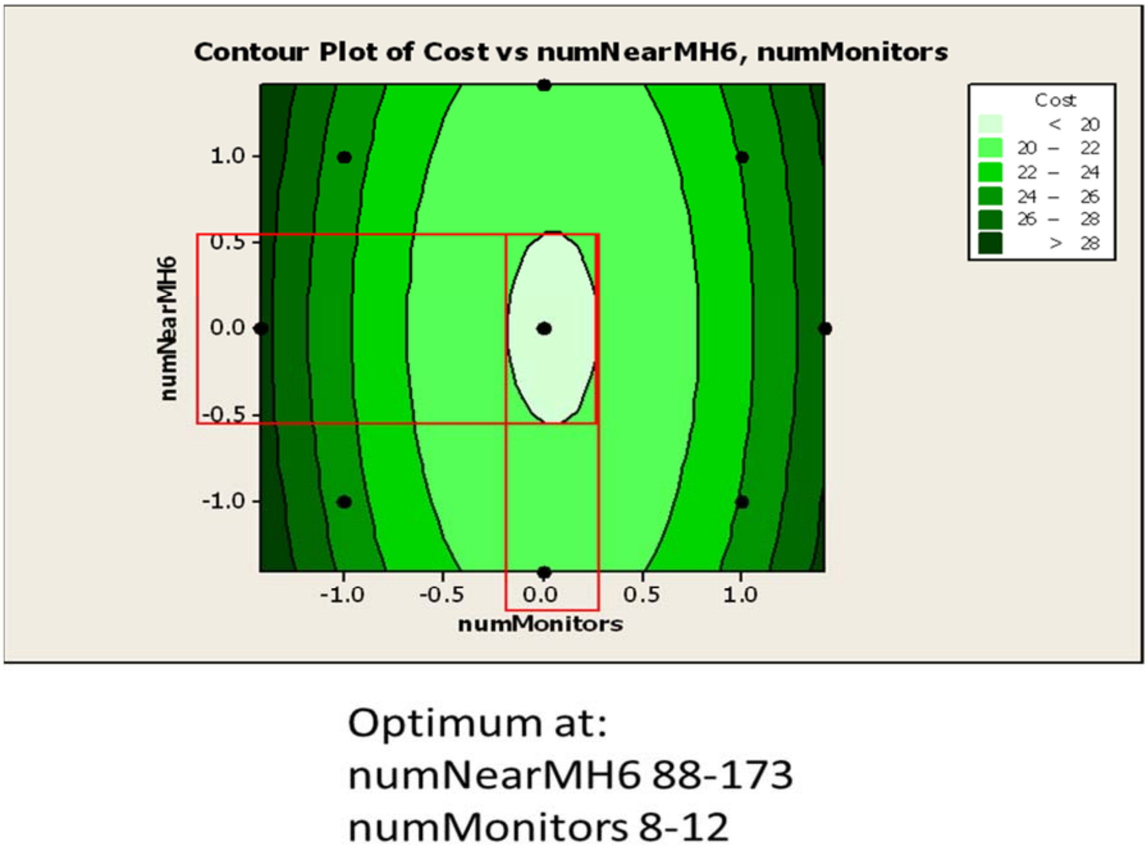

Figure 5-3: Contour plots at optimum

Next, an experiment was designed within the range of the optimum contour. The results showed only noise which suggests that the factors were not varied sufficiently in this range to produce a statistically significant response. This led to a judgement that the ranges were sufficiently precise to estimate optimal parameters and no further excursion experiments were performed.

At this stage, all experimental runs with the ESA algorithm were combined and graphically analyzed. An interesting observation was discovered showing the relationship between numMonitors, the number of iterations required to meet the objective function constraints, and the cost response variable. This insight is the basis of several conclusions discussed elsewhere in this chapter, and the understanding of tradeoffs between cost and other objectives that may be valued by sewer system operators.

5.1.6 Optimum parameter settings

A summary of factor levels that produced the minimum cost is shown in table (5-5). The values in grey font were not significant. They were held at the shown midpoint values during the optimization experiments.

Table 5-5: Factor levels producing minimum cost

Parameter	BSA-Hood	BSA-Dist	ESA
numMonitors	5	1	100
coolingRate	10	0.1	10
rangeValue1-4	1 hood	15,000	500
rangeValue5	50 MH	15,000	500
rangeValue6	1 hood	500	500
rangeValue7	2 hoods	500	500
rangeValue8+	1 hood	500	500
numNearMH6			130

As seen from the above table, the two base simulated annealing algorithms produced better results at levels of numMonitors less than or equal to 5. In comparison the enhanced simulated annealing algorithm performed better at a much higher level of 100 numMonitors. The reason behind such difference is that the ESA algorithm uses severity rating information to confine the initial placement of monitors to a subset of locations that are more likely to have high RPN values, while the BSA algorithms randomly distribute the initial placement across the entire sewer network. This difference produced a significantly different strategy in how the ESA searched for a solution in contrast to the two BSA algorithms. On the other hand, the differences in numMonitor settings between the two BSA algorithms was not practically significant to the cost response. The reason for the difference in optimal parameter settings is related to the fact that the BSA-Dist algorithm is less restrictive for movement while BSA-Hood enforced network connectivity and geographic neighborhood restrictions. Hence, agents more often exhausted the candidate locations to move to and ceased to search further.

The coolingRate parameter produced smaller effects on the response variable than did numMonitors. For the ESA algorithm, the coolingRate was not statistically significant while for the BSA algorithms it served two functions. The first function was to allow the movement to worse solutions in order to escape local minimums. The second function was to terminate the simulation when the temperature variable became less than 1. Therefore, for the BSA-Dist algorithm, the coolingRate converged to a very low setting to allow each monitor enough iterations to find 50 manholes with an RPN greater than or equal to 50. For the BSA-Hood algorithm, the coolingRate did not need to go as low due to the optimal results occurring with numMonitors = 5.

The rangeValue and numNear parameters controlled the magnitude of the movement allowed by the agents as a function of their current location's RPN. These differences in the settings highlight two general observations. First, the sensitive bins for the movement were those around the threshold value of RPN. Although this was a statistically significant factor in the BSA-Dist and ESA algorithms, the BSA-Hood algorithm operated differently as the sensitive parameters were the bins immediately before and after rangeValue6. The second observation is that smaller movement at bins equal to and above the threshold bin produced better results due to the clustering of risk. Once an agent discovered a high-risk location, its best movement strategy was to search nearby manholes for the next move.

5.1.7 Performance comparison

The interval plot in figure (5-4) depicts the mean cost and 95% confidence intervals for the mean for each of the three simulated annealing algorithms.

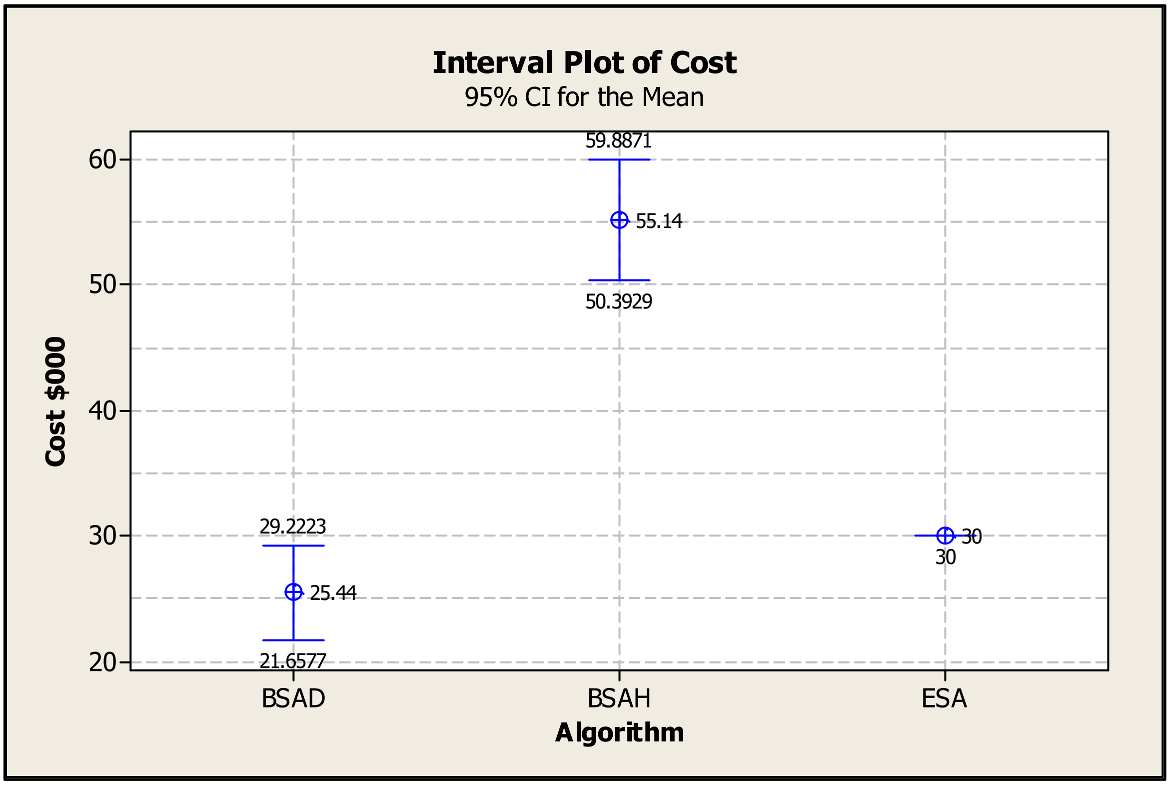

Figure 5-4: Interval plot of cost

The interval plot was produced by 10 replications of each algorithm at its optimal settings. There are no overlapping confidence intervals for the 10 replicates of each algorithm which indicates statistically different mean cost responses. The BSA-Dist algorithm produced the lowest cost, while the ESA algorithm was slightly higher than the upper limit of the BSA-Dist confidence interval, by less than $800. However, a major difference between these two algorithms is that the that the results from the BSA-Dist were more variable than ESA. The reason behind this difference is that for the former algorithm, there are low number of monitors, 1, which makes many iterations across a space that varies in each simulation run. In contrast, the ESA algorithm exhibited the ability to meet the objective function constraints with the initial placement of agents. This yielded some desirable properties in addition to reaching a cost response that was second best of those found in these experiments.

The BSA-Hood algorithm produced significantly worse results than the other two algorithms. It was observed that the BSA-Hood algorithm was less stable in terms of terminating before either finding a solution or running out of memory in the simulation, albeit no statistics were kept on these problems.

5.1.8 Insights gained in optimization experiments

The intensive experimentation with the simulated annealing algorithms revealed several potentially important insights into the optimal sensor placement. These insights are as follows.

5.1.8.1 There are significant trade-offs to achieving the lowest average cost

5.1.8.1.1 There is a trade-off between lowest mean cost and variability of cost

As seen from figure (5-4), there is a trade-off between the cost variability and the lowest average cost. From this figure, it is evident that the BSA-Dist had the lowest average cost with a mean cost of $25,400. Yet, this low mean cost was accompanied with a standard deviation of $5,300 and a coefficient of variation of 21%. On the contrary, the ESA algorithm produced a higher mean cost of $30,000, yet with zero standard deviation.

5.1.8.1.2 There is a trade-off between lowest mean cost and search duration

As shown in figure (5-5), there was a significant difference in the duration of the search depending on the employed algorithm. The lowest cost algorithm, BSA-Dist, yielded the longest duration with a mean of nearly 85 months and a standard deviation of 17.6 months. In comparison, the ESA algorithm met the objective function constraints in 1 month with zero standard deviation. This is a significant difference that warranted further exploration as outlined below.

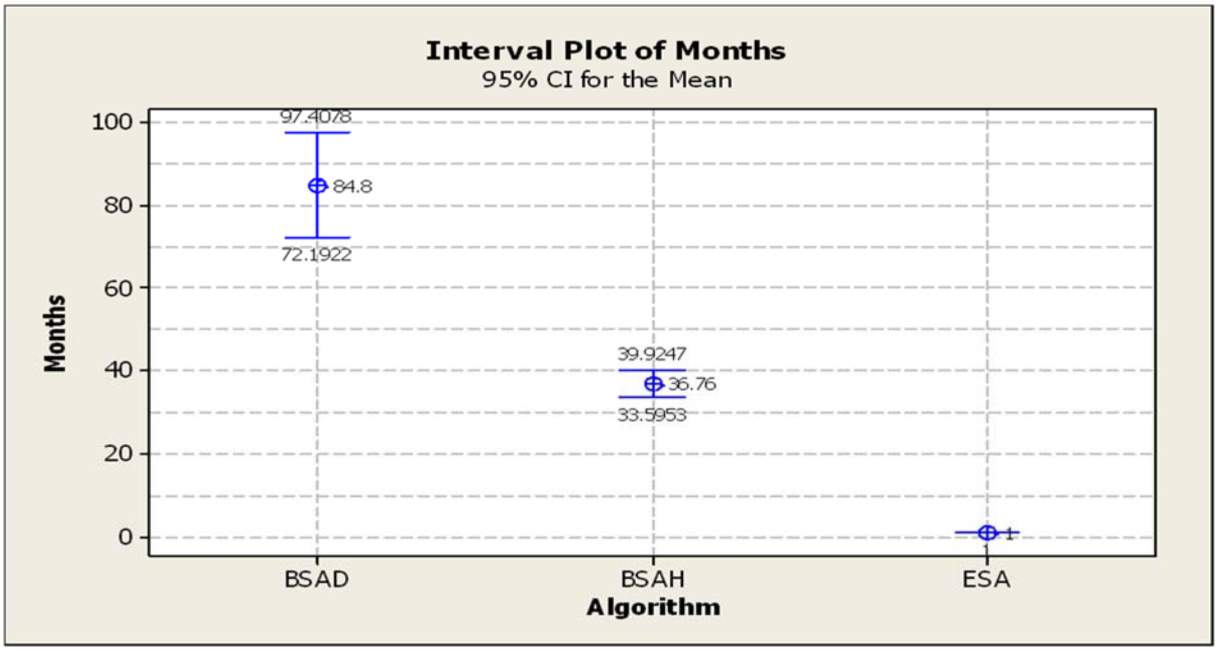

Figure 5-5: Interval plot of duration

As explained previously, fewer meters are more efficient in terms of cost but take more time due to “the resolution problem” which is the phenomenon of overshooting the objective function constraint. To demonstrate the impact of this phenomenon in the context of this research, scatterplots of cost and duration were drawn as presented in figure (5-6) for the BSA-Dist algorithm.

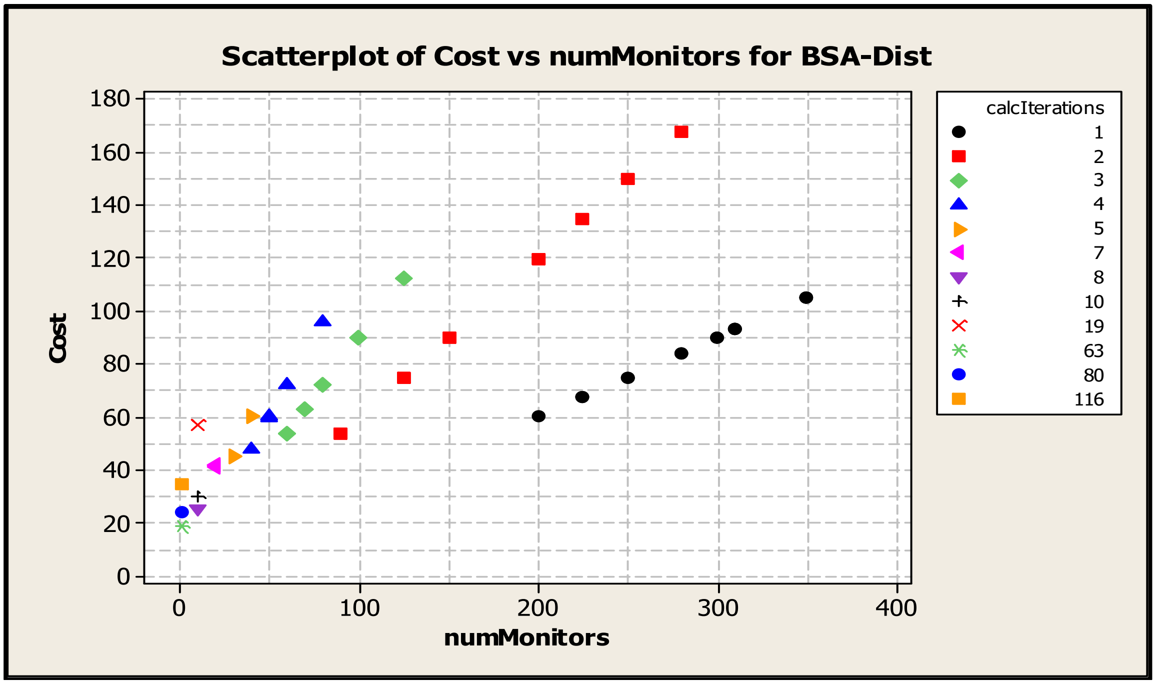

Figure 5-6: Scatterplot of cost & duration for the BSA-Dist algorithm

In order to accurately draw this plot, a new response variable, calcIterations, was created to store the number of iterations (months) required for a simulation to meet the objective function constraint. A number of patterns are visible. First, as the number of monitors increases, the calcIterations decrease as expected. Second, the average cost follows a pattern of increase with increasing numMonitors until a critical value is reached that enough monitors are employed to insure consistently finding a sufficient number of locations to meet the constraint on a particular number of iterations. A clear example of this pattern is shown in the case of the BSA-Dist algorithm in figure (5-6). As seen from the figure, at 200 numMonitors on the x-axis, the cost is sometimes equal to $60,000 and in other simulation runs reaches $120,000. These are the different costs to conduct either one or two iterations of monitoring. As the number of the monitors is increased, it can be seen that the cost increases for both the one and two iterations, which is expected. This trend continues until the numMonitors reach 300. At this level, all of the simulation runs achieve the objective function in a single iteration. Thus, the average cost decreases because no 2-iteration runs exist to raise that average. Moreover, this is also considered the point of minimum iterations as adding monitors beyond this point will only add cost.

In the case of numMonitors equal to “1”, the algorithm will stop when the constraint is met exactly. For example, the BSA-Dist algorithm with one agent always stopped exactly when the 50th location meeting the RPN criteria was located. The last iteration that discovered the 50th location would have a cost of only \$300 * 1 = \$300. However, in the scenario where numMonitors is equal to 100, the extra iteration that contained the 50th location costs \$300 * 100 = \$30,000. Yet, in treatments with a high number of monitors, extra locations above the required number of 50 were common because the “resolution” of the simulation runs was in 100-agent, \$30,000 units.

In addition, a similar pattern is observed in the scatterplot of cost and duration for the ESA algorithm as shown in figure (5-7).

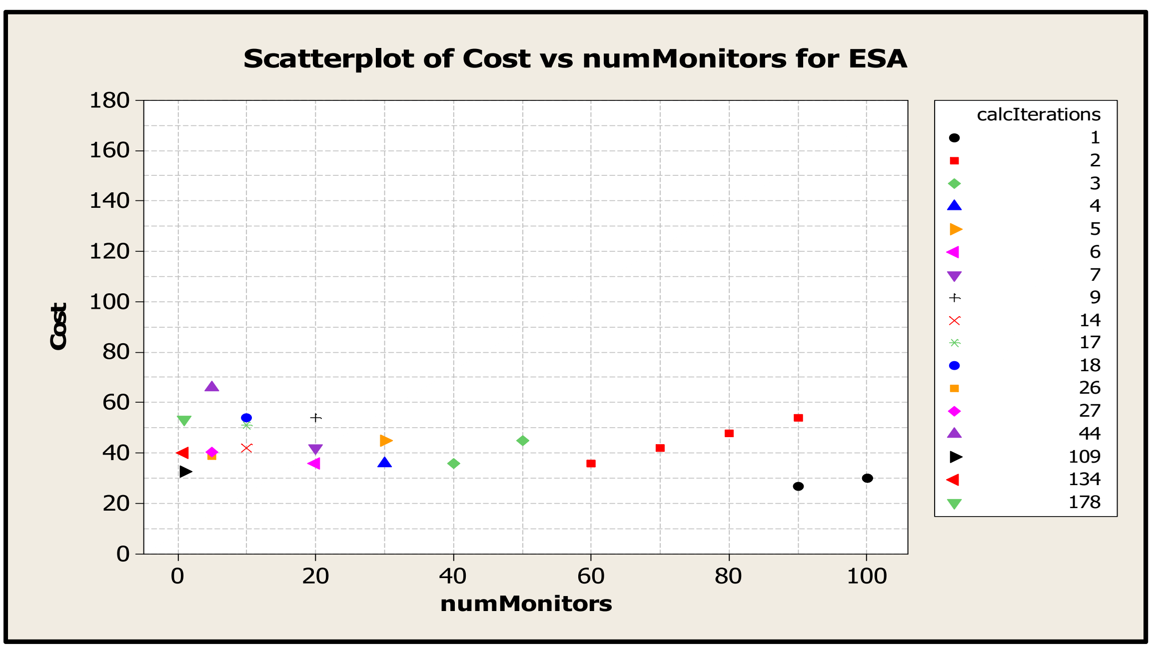

Figure 5-7: Scatterplot of cost & duration for the ESA algorithm

In this figure, the ESA reaches the point of 1-iteration solutions at the level where the numMonitors is equal to 100, which is one-third the number of iterations required by the BSA-Dist algorithm. This advantage in duration was achieved as a result of the ESA algorithm's limitation of the search space in the initial placement of monitors, while the BSA-Dist algorithm selects initial locations from among the entire system. For the BSA-Dist algorithm, as the number of monitors increases, the probability of selecting an initial location with an RPN equal to or greater than the threshold RPN converges on the probability of those locations existing in the entire population of locations. Since the ESA algorithm prioritizes initial locations based on severity ratings, the proportion of locations with RPNs meeting the threshold RPN becomes significantly higher in locations with high severity ratings. Therefore, the probability of initially placing a monitor in a high RPN location is much higher in the ESA algorithm.

5.1.8.2 Improvements can be made through enhancements to the simulated annealing algorithm

The discovery of desirable outcomes in terms of variation and duration led to an analysis of the three algorithms performance over multiple objectives. Table (5-6) presents a ranking of the three algorithms at various levels of numMonitors based on cost (labelled "avgAdjCost"), coefficient of variation for cost (labelled "COVadjCost"), and duration in months (labelled "avgCalcIterations"). From this table, it can be concluded that the ESA algorithm with 100 monitors achieved the best outcomes for variation and duration and the 2nd best outcome for cost. Moreover, the BSA-Dist algorithm achieved the best ranked outcome for cost, but the 26th ranked variation and the 31st ranked duration. The last column is a logical check for dominated solutions, which shows that there are only two treatments that are non-dominated.

Table 5-6: Ranking of the three algorithms at various levels of numMonitors

Algo	numMonitors	avgAdjCost	COVadjCost	avgCalcIterations	costRank	covRank	iterRank	rankSum	Nondominated
ESA	100	30.0	0.00	1.00	2	1	1	4	TRUE
ESA	60	36.0	0.00	2.00	3	1	10	14	FALSE
ESA	70	42.0	0.00	2.00	7	1	10	18	FALSE
ESA	40	36.0	0.00	3.00	3	1	16	20	FALSE
ESA	80	48.0	0.00	2.00	14	1	10	25	FALSE
BSAD	300	90.0	0.00	1.00	24	1	1	26	FALSE
BSAD	90	54.0	0.00	2.00	17	1	10	28	FALSE
ESA	50	45.0	0.00	3.00	11	1	16	28	FALSE
BSAD	310	93.0	0.00	1.00	28	1	1	30	FALSE
BSAD	350	105.0	0.00	1.00	31	1	1	33	FALSE
BSAD	150	90.0	0.00	2.00	24	1	10	35	FALSE
BSAD	30	45.0	0.00	5.00	11	1	25	37	FALSE
BSAD	70	63.0	0.00	3.00	21	1	16	38	FALSE
BSAD	100	90.0	0.00	3.00	24	1	16	41	FALSE
ESA	90	45.0	0.35	1.67	11	27	8	46	FALSE
ESA	30	42.0	0.12	4.67	7	17	23	47	FALSE
BSAD	20	41.8	0.01	7.00	6	16	26	48	FALSE
BSAD	50	59.9	0.00	4.00	19	15	22	56	FALSE
BSAD	1	25.9	0.31	86.33	1	26	31	58	TRUE
BSAD	40	56.0	0.12	4.67	18	17	23	58	FALSE
ESA	20	44.0	0.21	7.33	10	22	27	59	FALSE
BSAD	60	60.0	0.17	3.33	20	20	20	60	FALSE
BSAD	225	90.0	0.43	1.33	24	31	5	60	FALSE
BSAD	125	87.5	0.25	2.33	23	23	15	61	FALSE
BSAD	80	80.0	0.17	3.33	22	20	20	62	FALSE
BSAD	250	100.0	0.43	1.33	29	29	5	63	FALSE
ESA	10	49.0	0.13	16.33	16	19	29	64	FALSE
BSAD	10	37.4	0.46	12.33	5	32	28	65	FALSE
BSAD	200	100.0	0.35	1.67	29	28	8	65	FALSE
ESA	1	42.1	0.25	140.33	9	24	32	65	FALSE
BSAD	280	112.0	0.43	1.33	32	29	5	66	FALSE
ESA	5	48.5	0.31	32.33	15	25	30	70	FALSE

Based on the above, the substantial improvement in the variability and duration with the ESA algorithm with a 1-iteration solution is very likely worth the increase in cost except in the case where duration is of almost zero weight to the decision maker.

Another benefit of the ESA algorithm with a single-iteration solution is its simplicity. In this case there are no movements of agents. This removes any affect from coolingRate, rangeValue, or numNearest parameters. The only parameter of consequence is the numMonitors.

To validate this conclusion, additional analysis was conducted in the region of numMonitors between 1 and 100 to confirm the ESA algorithm's performance. The interval plot in figure (5-8) visualizes the relationship between cost, numMonitors, and number of iterations. The numeric labels on the plot represent the number of iterations in months. From this plot, as the numMonitors increases, the variation decreases to a point around a consistent duration. Afterwards, the variation will start increasing again as the number of monitors begin to reach for a lower number of iterations. Hence, the ultimate solution is the one that requires a minimum numMonitors to reach a solution with a single iteration. This was achieved at a cost of $30,000 and 100 numMonitors.

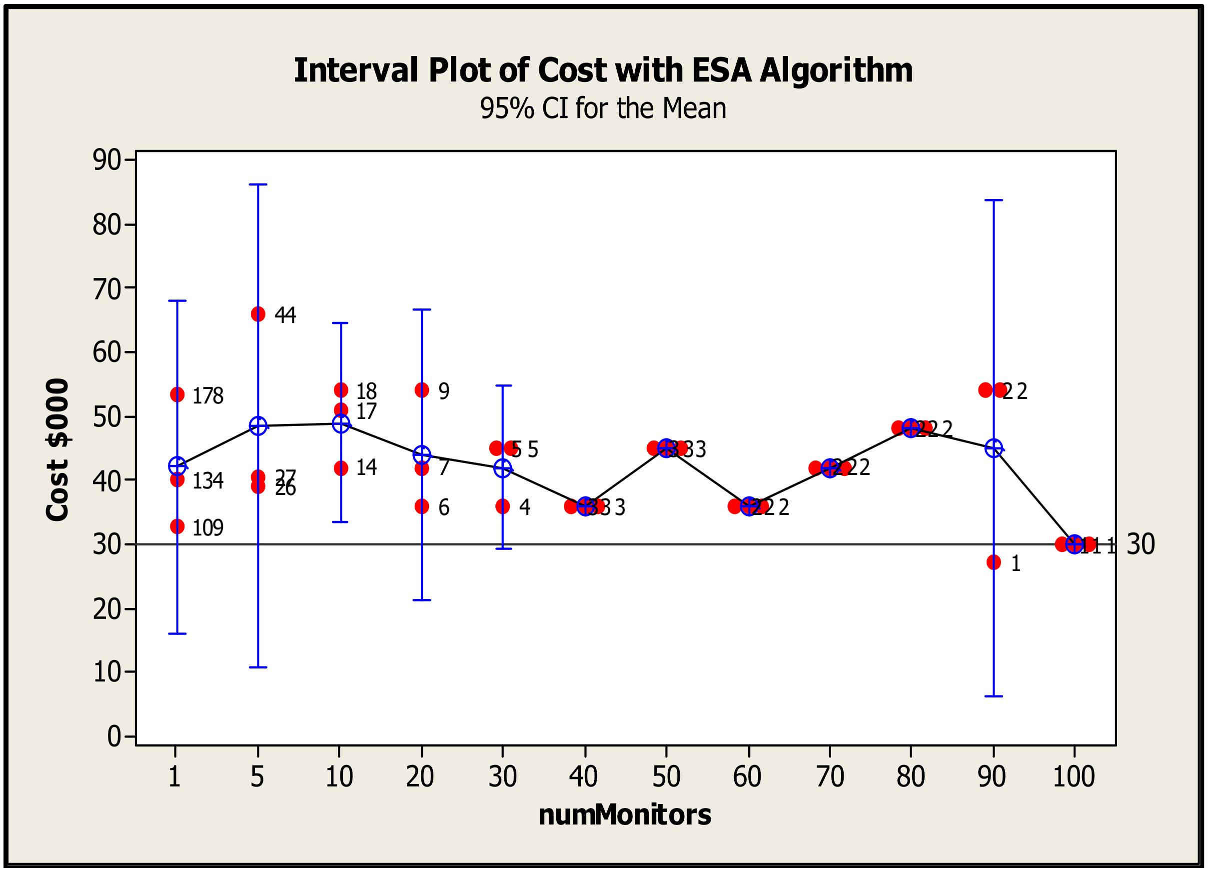

Figure 5-8: Interval plot for the ESA algorithm depicting the relationship between cost, numMonitors, and number of iterations

5.1.8.3 There are diminishing returns of successive iterations

It was observed that diminishing returns occurred at micro and macro levels. On the micro level, there are diminishing returns in successive iterations within a simulation run. This observation was evident when the run-time output of the simulation was depicted in figure (5-9) for the example case of 5 agents in the ESA algorithm. This graph plots the cumulative number of locations discovered that meet the threshold RPN requirements, which is represented by the gold line. The red line represents the threshold RPN. Hence, when the red line becomes a vertical line, this means that the minimum number of qualified locations has been located. As seen from the figure, the number of risky locations discovered initially increases on a steep slope then it starts to flatten. This can be attributed to the fact that the logic of the search algorithm limits the search area to a potential hot spot when risky locations are found. Although this figure demonstrates this pattern for the ESA algorithm, a similar pattern of diminishing returns was observed in all simulated annealing algorithms.

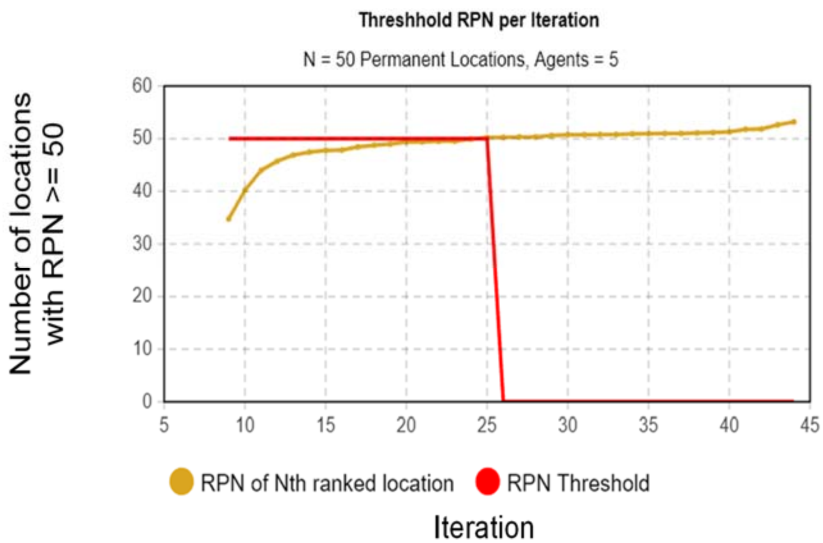

Figure 5-9: Run-time output of the simulation

On the macro level, a second diminishing return was observed in the relationship between duration and the number of monitors. Figure (5-10) represents a regression fit of the relationship between duration and numMonitors for the BSA-Dist algorithm. The Morgan-Mercer-Flodin model provides a good fit to characterize this relationship with a coefficient of determination, r^2, for the BSA-Dist and ESA models fit of 0.93 and 0.95, respectively. As observed from the figure, the model shows a rapid improvement for each additional monitor added when numMonitors is small, with diminishing returns after an inflection point.

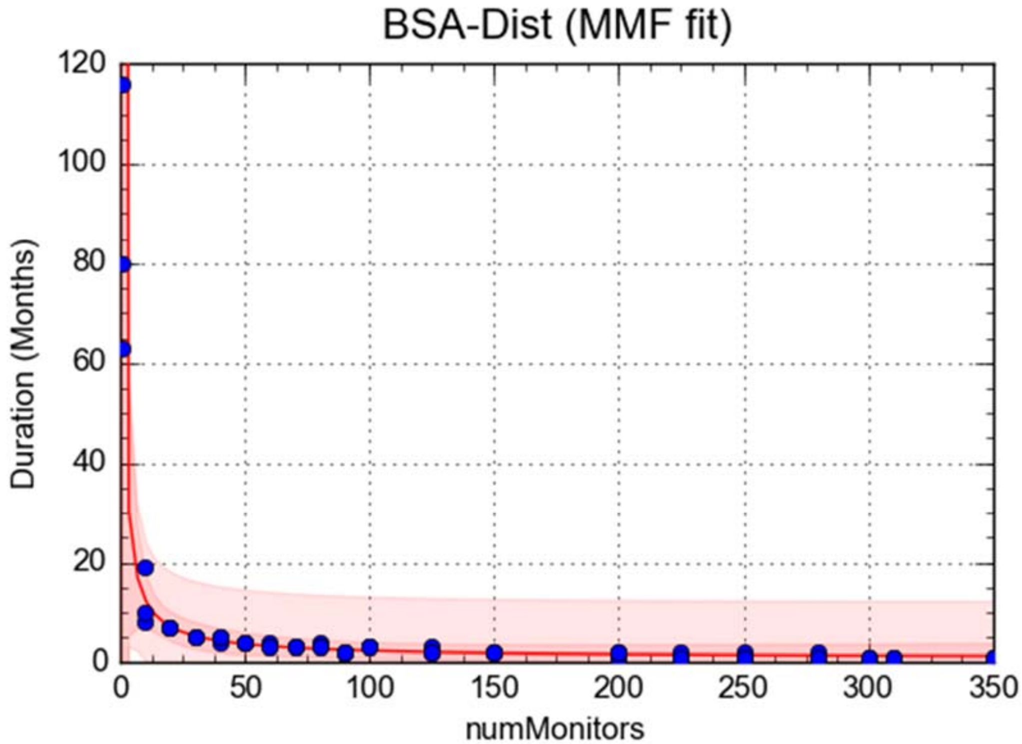

Figure 5-10: Fit of the relationship between duration and numMonitors for the BSA-Dist algorithm

In addition, figure (5-11) depicts the relationship between the duration and the numMonitors for the ESA algorithm. While the shapes of the curves are very similar, the x-axis scale is substantially smaller in the case of the ESA algorithm due to the reasons discussed above.

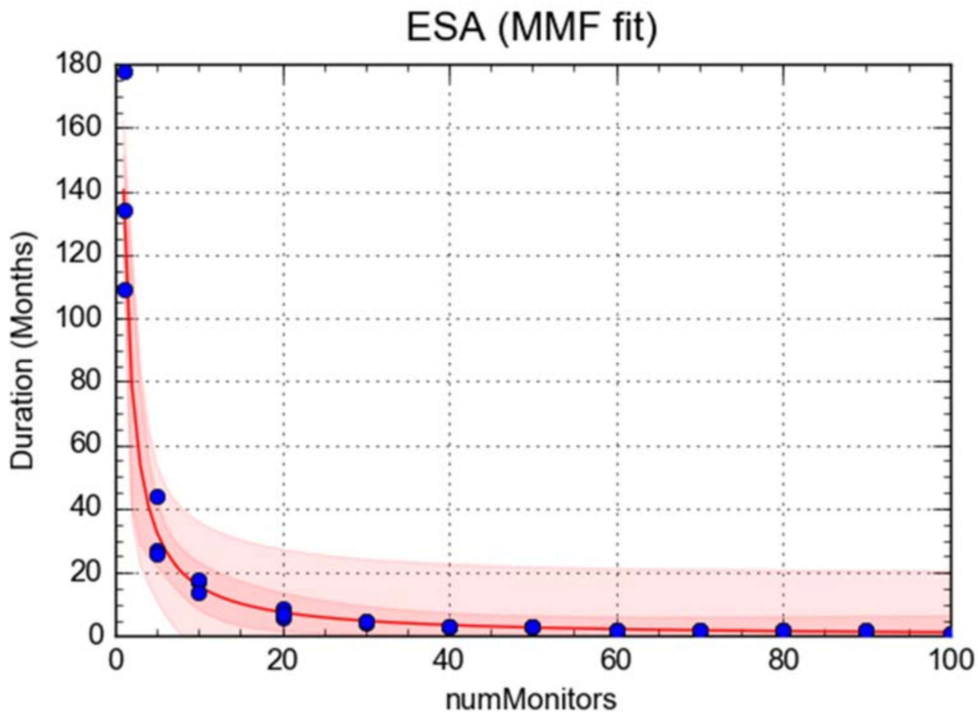

Figure 5-11: Fit of the relationship between duration and numMonitors for the ESA algorithm

5.2 Optimization of sequential search parameters

The objective for iincorporating a sequential search algorithm into the simulation is to compare its performance to that of the enhanced simulated annealing metaheuristic. Sequential search models are a common industry practice for conducting closed circuit television inspection of pipelines beginning at the upper branches of the collection system network and working sequentially towards the termination of the network, usually at wastewater treatment plants.

The simulation was developed with four parameters for the sequential search (SS) algorithm. Each parameter combination was replicated three times in order to measure the performance across variable locations of hot spots and various starting locations. Finally, for each simulation run, the cost, number of inspections, and duration were recorded.

The first of these parameters is the number of permanent locations (numPermenantLocations). This parameter represents the number of locations being searched for in excess of the minimum RPN threshold. In these simulation runs this parameter was kept constant at a value of 50 in order to provide a direct comparison to the ESA results. Similarly, the second parameter, the RPN threshold (minRPNThreshold), was also kept constant at a value of 50. Regarding the third parameter, the number of inspectors (numInspectors), this parameter was varied in the simulation from 1, 10, 20…,100 to explore the effect of the number of inspectors on the cost. A total of 45 simulation runs were used to assess the sequential search algorithm's performance.

The fourth parameter is the cost per inspection (costPerIteration) which is equivalent to the cost per monitoring location in the ESA algorithm. In order to determine the value for this parameter, two inputs were considered; the average inspection cost and the inspection productivity as a function of time. For the first input, data for closed Circuit Television (CCTV) inspection was available from two sources to arrive at an estimated unit cost for inspection. Table (5-7) is reproduced from the 2004 U.S. EPA Report to Congress (US EPA 2004a). Costs per foot of inspection exhibited a wide range, from $0.27 to $3.24. The average cost per foot of $1.44 in 2002 was used in this analysis. However, before using this average cost, an adjustment was made to convert this amount to the current 2018 dollars. Based on the U.S. Bureau of Labor Statistics inflation calculator, the average cost per foot for the inspection was calculated to be $1.99 in 2018 dollars. In addition, a second conversion was required to convert the cost per linear foot into an equivalent cost per manhole. A study published by the engineering firm Black and Veatch in 2000 concluded that there were 22.3 manholes per mile of sewer pipe, or an average of 236 feet of pipe per manhole (Nelson, Habbian, and Andrews 2000). This is consistent with the GIS database provided for this research where a reported 3,036,000 feet of pipe contained 14,446 manholes, or an average of 210 feet of pipe per manhole. Consequently, the higher number of 236 feet was used in this analysis. Therefore, by using the cost estimate of $1.99/linear foot and 236 linear feet/manhole produces an equivalent manhole cost of $470/manhole. This value was used for cost per inspection.

Table (5-7): CCTV cost per linear foot including labor and equipment costs

Location	**CCTV Cost ($)**
Los Angeles, CA	0.57
Sacramento, CA	1.63
Santa Rosa, CA	0.27
Honolulu, HI	3.24
Boston, MA	1.89-2.70
Laurel, MD	1.72
Albuquerque, NM	1.56
Charleston, SC	0.39
Fort Worth, TX	0.48
Fairfax County, VA	0.81
Norfolk, VA	1.62
Virginia Beach, VA	1.56-1.73
Average	1.44

Inspection productivity was estimated in order to assess the duration to meet the objective function. CCTV inspection data was provided by a CCTV contractor derived from decades of history across multiple cities. Their productivity assumption was that a single crew can inspect 1,200 feet of pipe per workday on average. Thus, given the assumption of 236 feet between manholes, this would equate to a crew inspecting 5.1 manholes per day.

5.2.1 Cost response

As shown from the linear regression fit in figure (5-12), there was no relationship found between cost and the number of inspectors.

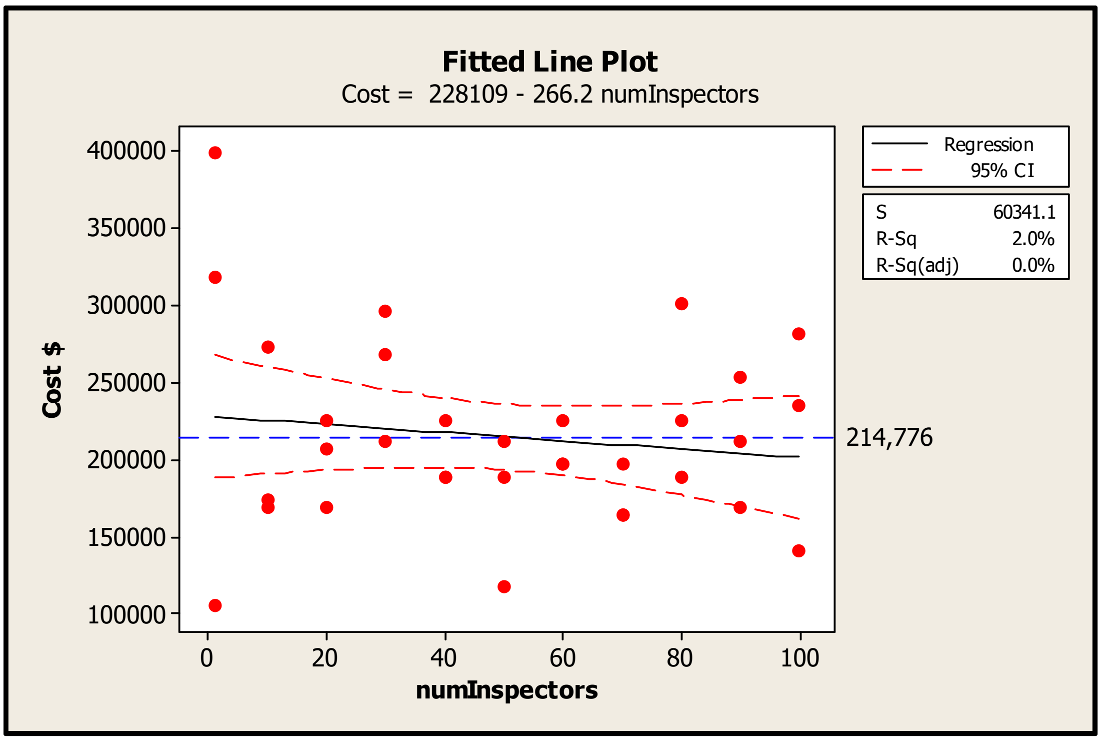

Figure 5-12: Fit of the relationship between cost and number of inspectors

From the regression analysis, the variation in the number of inspectors explained only 2% of the variation in cost as indicated by the r^2 statistic. The red dotted lines in the above figure depict the 95% confidence intervals for the regression line, shown in black, while the blue dotted line is the average cost for all runs of $214,775. A horizontal line can be contained within the confidence interval boundaries, which is an indication of the lack of correlation with the number of inspectors. The 95% confidence interval for the mean cost was $194k - $236k. The cost analysis indicated that cost was driven simply by the number of locations that must be inspected to find 50 manholes with an RPN meeting the threshold conditions. The 95% confidence interval resulted in between 412 and 502 inspections were required on average to meet these conditions. The cost variability resulted from how close the agents were initially placed to hot spots based on the randomness designed in the simulation.

5.2.2 Duration trade-off

The conclusion that the cost was dependent solely upon the number of inspections performed plus a variance term, inferred that the duration of the search could be shortened by simply employing more inspectors. However, as the number of inspectors increased, the improvements in duration due to extra inspectors was lost in the variance component. After 70 inspectors there was no statistical difference in the duration of the search. These results are presented in table (5-8).

Table (5-8): Inspection duration trade-off

numInspectors	Duration LL	Duration UL	Bin
100	0.6	1.3	1
90	0.8	1.2	1
80	0.9	1.6	1
70	0.9	1.2	1
60	1.3	1.6	2
50	1.0	1.9	1
40	1.9	2.4	3
30	3.0	4.4	4
20	3.6	5.0	4
10	5.9	11.5	5
1	43.8	189.5	6

5.2.3 Variability trade-off

An analysis of the variability of the cost as a function of the number of inspectors showed there is no statistical difference as evident by the overlapping interval bars in figure (5-13). The high p-values shown for the Bartlett’s Test and Levene’s Test are further evidence of the equality of variances at different levels of numInspectors. The null hypothesis is that the population variances under consideration are equal, and the alternative hypothesis is that not all variances are equal. The high p-values lead to a rejection of the null hypothesis.

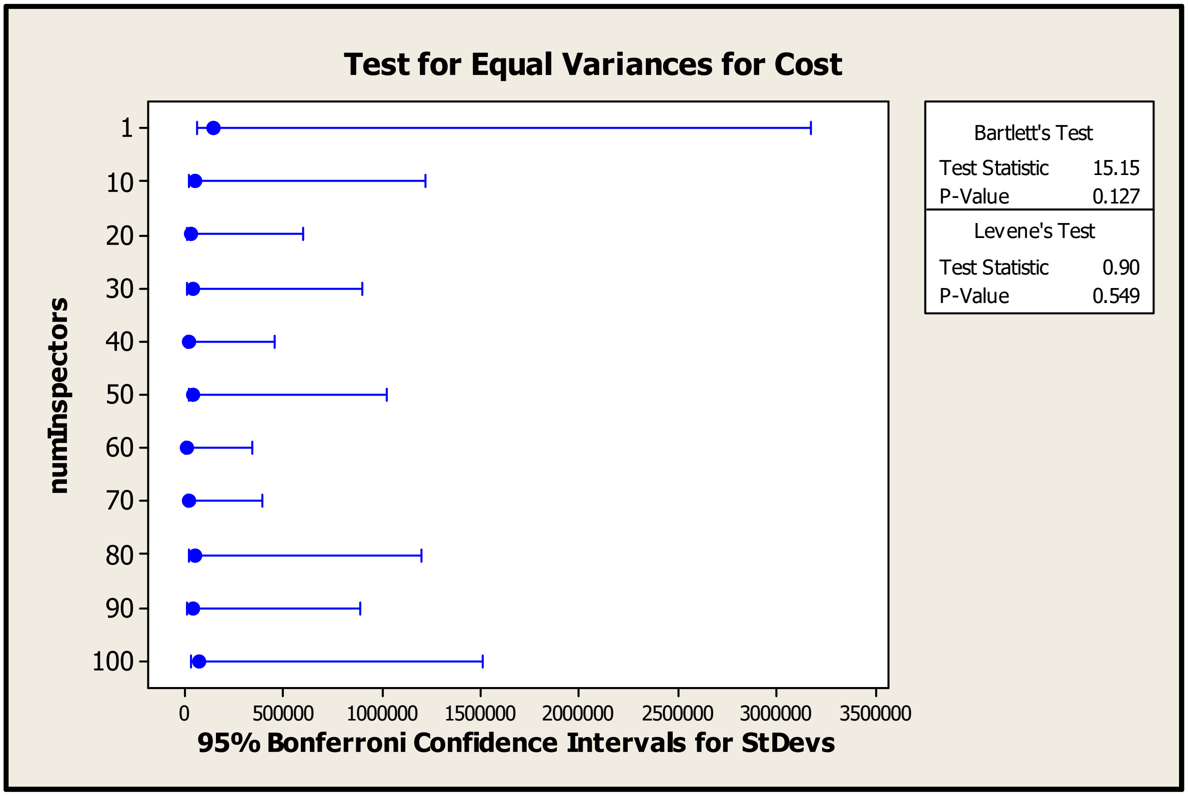

Figure 5-13: Test for equal variances of the relationship between cost and number of inspectors

5.2.4 Comparison to the ESA algorithm

Using the cost and productivity assumptions described above, the ESA algorithm met the objective function at a significantly less cost, \$30k for ESA, versus \$215k for SS. This suggests that significant cost savings could be achieved by replacing CCTV inspections with level monitoring. Based upon the conclusion that on average 457 pipe segments would be required to meet the constraints of the simulation conditions, inspection cost would have to decrease from the assumed value of \$1.99/foot to

$0.28/foot in order to achieve cost parity with the ESA approach. This conclusion would also require the bold assumption that a point-in-time CCTV inspection would be as effective in estimating risk occurrence ratings as 30 days of continuous level monitoring.

In terms of duration, the simulation concluded that between four and five inspection crews could meet the objective in one month, which was the time required by the ESA approach. The only advantage offered by the sequential search approach was that the addition of more inspectors will enable the completion of the work in less than one month, which was the minimum duration using ESA. This, however, was not proven by the simulation because the duration savings were sufficiently small to be lost in the noise of the simulation randomness.

5.3 Optimization of greedy search parameters

The purpose of incorporating a greedy search algorithm into the simulation was to judge the benefits of the optima-escaping features of simulated annealing, namely its probabilistic allowance of movement to inferior solutions. To achieve this objective, a series of simulation experiment runs were conducted using a greedy search algorithm. Initially, three replications of each treatment were run in order to calculate a mean cost and duration. Yet, to better understand the variation of the results, ten replications were run in the parameter settings that yielded the best outcomes.

The greedy algorithm employed operates with nearly identical logic to the base simulated annealing algorithm with the distance neighborhood function (BSA-Dist), except that the coolingRate parameter is not used and the simulation is terminated after 120 iterations. This number of iterations was assumed to be a sufficient because it represents 10 years of searching, which is much longer than a collection systems operator would be willing to wait based on the researcher's experience. Therefore, due to the similarity between the greedy algorithm and the BSA-Dist algorithm, all parameters, except for the numMonitors parameter, were held at the optimal levels discovered in the BSA-Dist experimentation described earlier. Figure (5-14) shows the screen shot of the simulation parameters for one of the three simulation runs with numMonitors = 1.

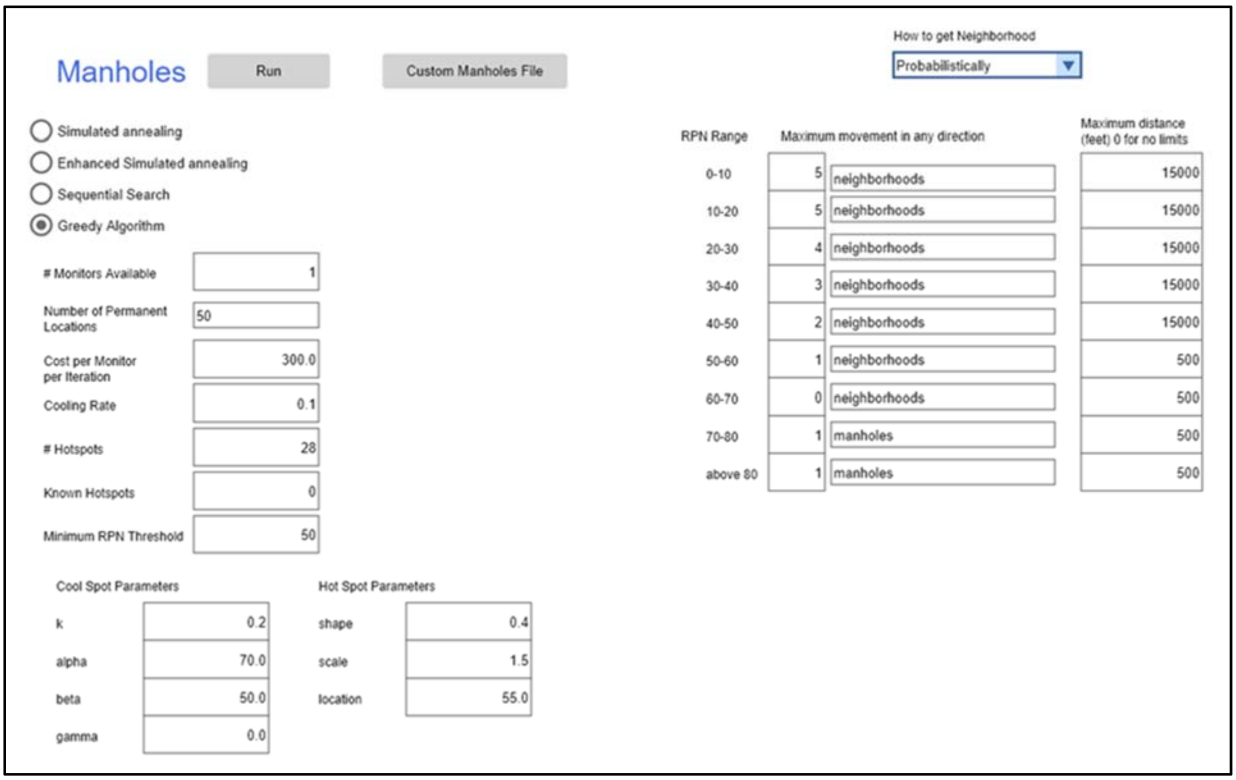

Figure 5-14: Screen shot of the greedy algorithm simulation parameters

5.3.1 Cost response

When conducting the simulation runs, those conducted at numMonitors =1 and numMonitors = 10 did not satisfy the objective function constraints before the 120-iteration limit was reached. Therefore, no results were available. These runs were removed from the experiment. The most likely cause of this result is that the greedy algorithm prevents movement to inferior solutions. Agents were likely trapped in locations of local optima that did not meet the minimum RPN threshold objective.

Figure (5-15) shows the interval plot of the cost response across the various levels of numMonitors. As seen from the figure, on average, fewer monitors produced a lower cost which is consistent with the BSA-Dist results. In addition, since the fewest number of monitors that would complete a simulation was numMonitors = 15, that level was accepted as the optimum setting. Also evident in the greedy algorithm was the phenomenon of the cost increasing as the number of monitors increases, until a point is reached that a sufficient number of monitors are employed to consistently reduce the number of iterations. For example, at the point of numMonitors = 220 the cost "resets" because the solution is found consistently in one iteration starting at that point.

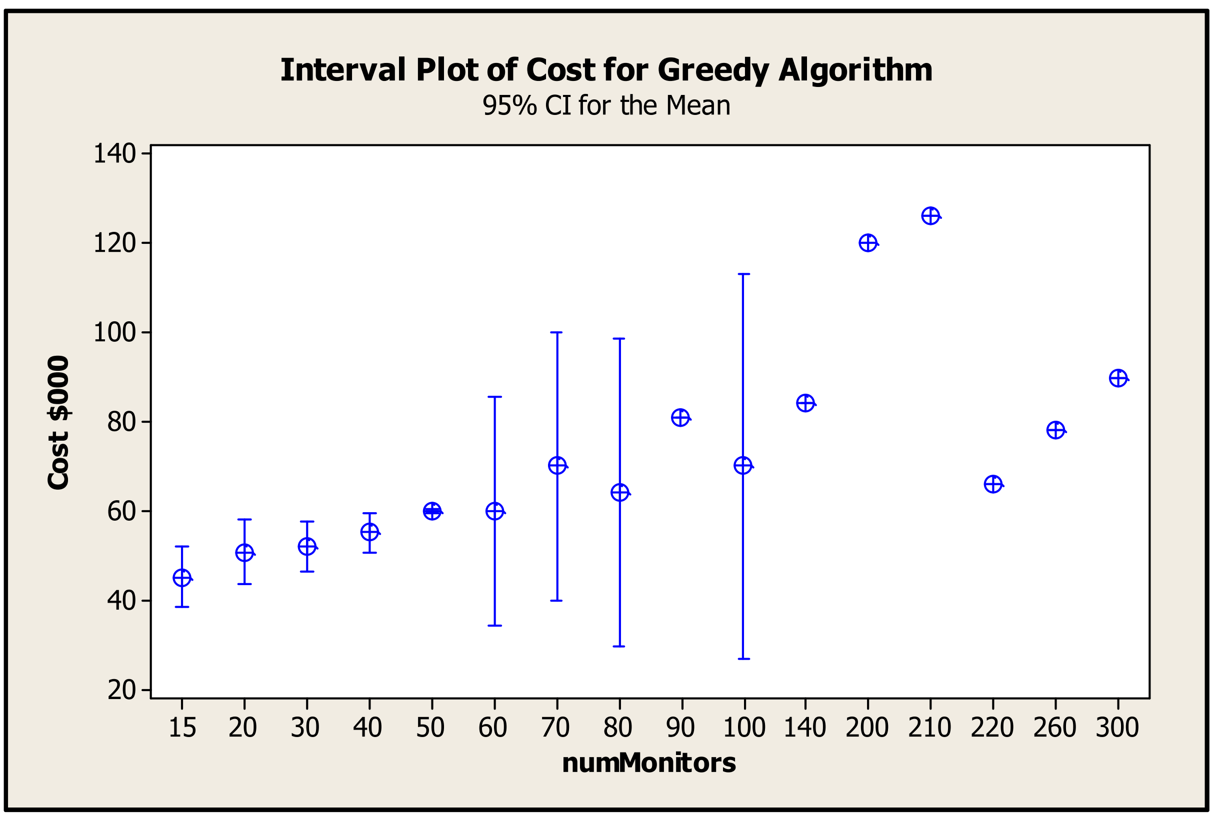

Figure 5-15: Interval plot of the cost for the greedy algorithm

5.3.2 Duration and variability trade-off

As seen from figure (5-16), there is a clear trade-off between the average cost and average duration in the greedy algorithm. In general, spending more money will decrease the duration of the search, which is consistent with the simulated annealing algorithms. A good compromise appears at the point where the average cost is equal to $66,000 and the average duration is one month. At this point, the level of monitors is 220, which was the lowest number of monitors that consistently achieved a 1-iteration solution. At the same time, the optimum solution which employs 15 monitors produces a lowest average cost of $45,000, but a longest average duration of just over 10 months.

Further analysis was also performed to compare the variability of the cost in relation to the number of monitors employed. From this analysis, and similar to the simulated annealing algorithms, the use of more monitors reduce variability after a certain point. These results are not discussed in this research study as they were not considered essential to the research objectives.

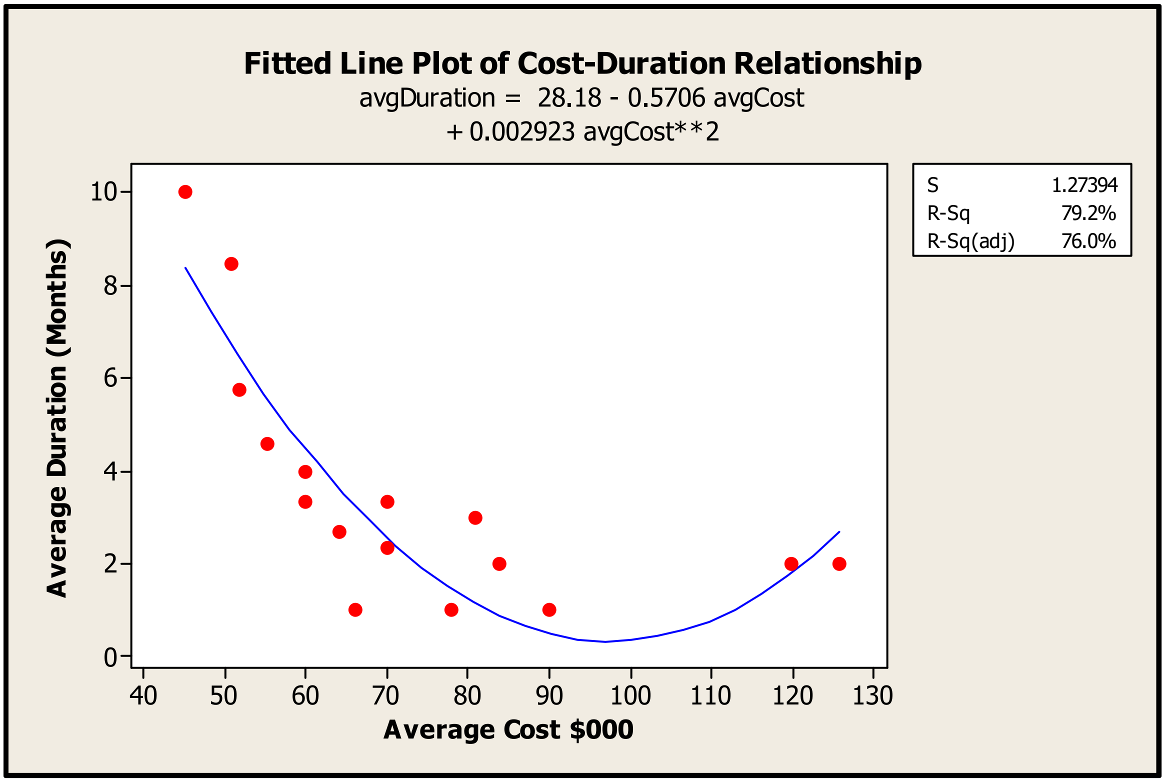

Figure 5-16: Regression fit of the relationship between cost and duration

5.3.3 Comparison of the greedy algorithm with other algorithms

The greedy algorithm was compared to the BSA-Dist algorithm using one monitor and also to the ESA algorithm using 100 monitors. Additionally, it was compared to a special run using the BSA-Dist algorithm with numMonitors = 15. This last configuration was used as a comparison “twin” to the greedy algorithm since it was the simulated annealing algorithm that matched the parameter settings of the best performing greedy algorithm configuration. Figure (5-17) displays the comparison in terms of cost. It is apparent that the performance at the optimal settings of the BSA-Dist and ESA algorithms are still significantly better in terms of mean cost than the greedy algorithm at the 95% confidence level. The BSA-Dist with 15 monitors produced a lower cost on average, yet the difference was not statistically significant at the 95% confidence level. However, the difference would have been significant at the 90% confidence level.

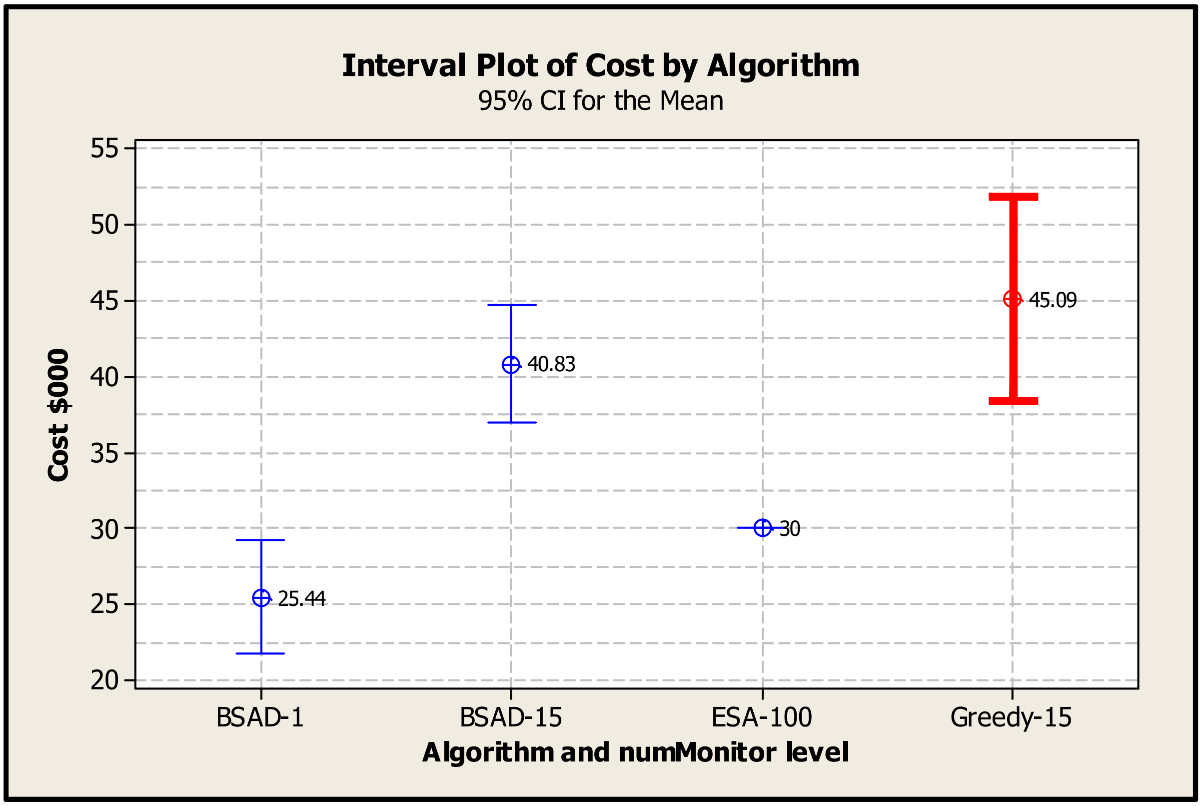

Figure 5-17: Comparison of the different algorithms by cost

In terms of duration, when analyzing trade-offs (figure 5-18), the greedy algorithm took 10.5% longer to achieve the simulation objective compared to the BSA-Dist algorithm with 15 monitors. Nonetheless, both were significantly inferior to the ESA performance that achieved the lowest possible duration of one month.

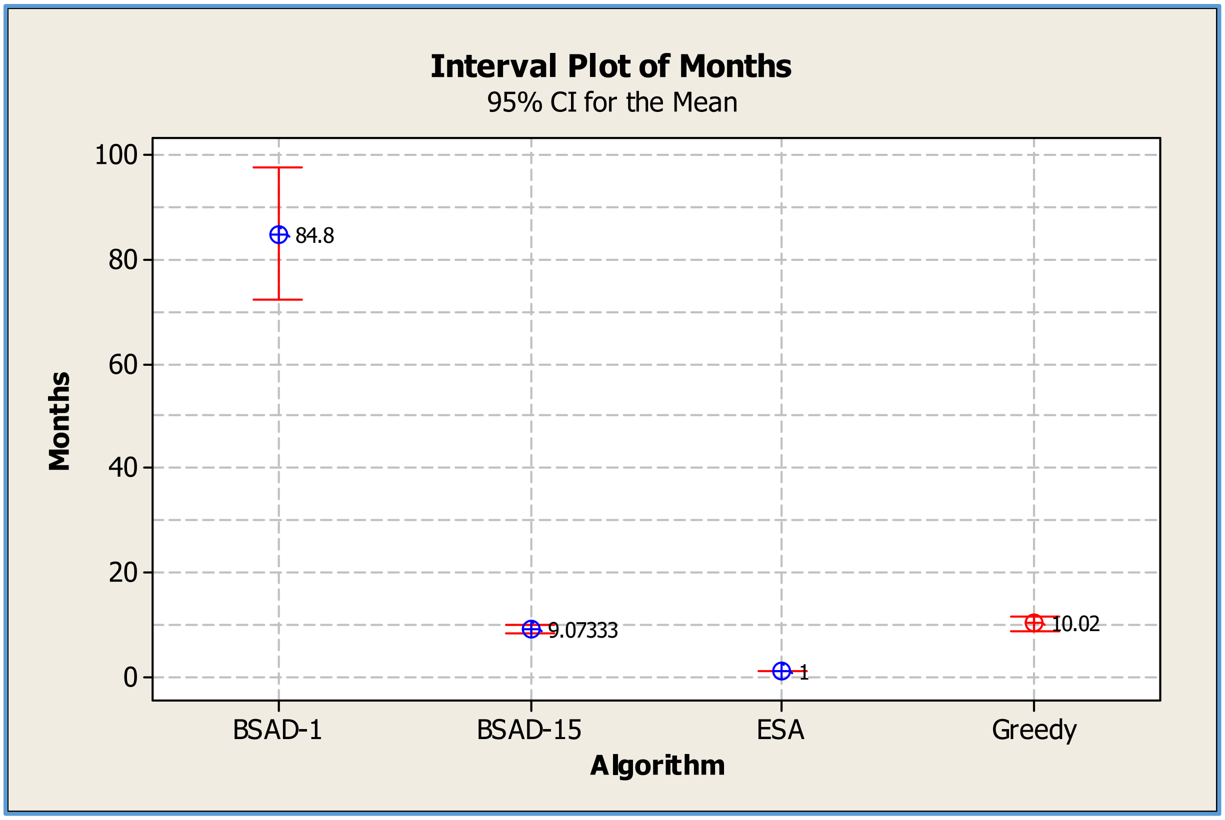

Figure 5-18: Comparison of the different algorithms by duration

In conclusion, there is an added value in the simulated annealing provision for movement to inferior solutions in early iterations. The cost increase of the greedy algorithm to its most closely matching simulated annealing algorithm was 10.4% with a similar inferiority in duration. Also, the greedy algorithm restricted movement to the extent that use of very small numbers of monitors would not find a solution in a reasonable time.

5.4 Sensitivity analysis

In order to gain a deeper understanding of the interrelationship of the search algorithm, sensitivity analyses were conducted in relation to; 1) the distribution of failure, 2) the chosen number of permanent locations, 3) the RPN threshold, 4) the number of known hotspots.

5.4.1 Sensitivity analysis for the distribution of failure

5.4.1.1 Simulation parameters involved in the RPN Distribution

The simulation was developed to accommodate changes in the number of hotspots, the hotspot parameters represented by the General Extreme Value distribution, and the coolspot parameters represented by the 4-parameter Dagum distribution, as shown in table (5-9).

Table (5-9): Hotspots and Coolspots parameters

Hotspot Parameters	Coolspot Parameters
Shape	Shape parameter (κ)
Scale	Shape parameter (α)
Location (μ)	Scale parameter (β)
	Location parameter (γ)

5.4.1.2 Assessing the sensitivity to RPN distribution

5.4.1.2.1 Experiment design

The purpose of the experiment was to determine which, if any, of the RPN distribution parameters affected the cost and duration of meeting the objective function and its constraints. The experiment design was a 7-factor, 1/8 fraction, 2-level DOE with a resolution IV. Table (5-10) presents each of the parameters used in the experiment and their respective low and high settings for the experiment runs, as well as a brief explanation for the reasoning used behind the choice of the different settings. Since there is no data available, these settings were based on the researcher's judgement on values that might be observed in actual sewer systems.

Table 5-10: The parameters used in the experiment

Parameter	Low	High	Reasoning
numHotSpots	19	57	Between 10% and 30% hotspots
K	0.1	3	Skewness of coolspots from left to right
A	50	90	Kurtosis for coolspots from flat to sharp
β	40	60	Variable top end of coolspot RPN

Parameter	Low	High	Reasoning
Γ			Held at zero to keep bottom end of coolspots at RPN of zero
ShapeX	0.1	0.8	Variable hotspot Kurtosis from flat to sharp
ScaleX	1	5	Range top end RPN in hotspots from 60 to 90
M	50	60	Set observed bimodality from non-observed to observed

There were 16 unique combinations of parameters in this experiment and each was replicated three times to account for the starting point variability present in the simulation experiment. All other simulation parameters were held at the optimal settings determined for the ESA algorithm.

5.4.1.2.2 Results

From this experiment, it was found that all seven factors had significant main effects on cost, as well as significant two-way interactions of the main effects. The main effects and the two-way interactions explained 97% of the variation in cost. In addition, based on the results, the most influential parameter was the coolspot scale parameter (β) as it accounted for 47% of the sequential sum-of-squares for main effects and was involved in 51% of sum-of-squares of the two-way interactions. For all experiment runs where beta was greater than or equal to 50, the resulting cost was at its minimum possible value of $30,000. In order to maintain optimal cost at low beta values, a high number of hotspots and a high coolspot shape parameter (κ) were required. Otherwise the results were highly variable.

In conclusion, the shape, scale, and location of coolspots and hotspots significantly affected the cost of the search for optimal locations. Each real application of this search will encounter different risk distribution. The implication of this conclusion is that in order to meet the objective function of minimizing cost across the full spectrum of real-world situations, a method is needed to estimate the distribution of RPNs so that the ESA search parameters, namely numMonitors, can be estimated.

5.4.1.3 Methods to estimate the distribution of RPNs in sewer systems

5.4.1.3.1 Attempts to estimate RPN distribution using 2 normal distributions

An expectation algorithm (EM) was studied to fit two normal distributions to the RPN data in which the lower distribution would characterize the coolspots and the higher distribution would characterize the hotspots. These normal distributions would be approximated by fits of a General Extreme Value distribution and Dagum distribution in the simulation. In this way, sample data could be approximately accurately in the simulation. However, the results of this methodology were inconsistent. For example, in one experiment run the cost using the optimization experiment parameters was consistently \$60,000 compared to \$90,000 using the EM estimated parameters.

In addition, it was apparent that gathering enough data to apply EM could become more expensive than the search for high RPN locations. In repeated trial and error, it appeared that about 200 locations would need to be sampled in order to get a reasonable approximation of the coolspot and hotspot parameters. Therefore, this approach was abandoned as being impractical.

5.4.1.3.2 Estimation of numMonitors based on proportion of high RPN manholes in small samples

As illustrated earlier in this chapter, the ESA algorithm produced the best results on single-iteration solutions. Those were the cases where the smallest number of monitors were located in areas with highest severity ratings such that the minimum number of qualified manholes were discovered in the initial placement. Based on this knowledge, an approach was designed that is based on estimating the proportion of high RPN manholes in the locations with the highest severity rankings.

The first step in this procedure was to determine the optimal setting of the numMonitors parameter for each of the 16 combinations of RPN distribution settings established by the DOE. For each of these combinations, the approach required multiple iterations of the simulation, with incremental changes in the numMonitors parameter, until a minimum inflection in cost was observed. Note that this approach is similar to the path of steepest descent procedure.

When a minimum was discovered, the detailed logs of the simulation were saved in a database for further analysis. From the database of simulation logs it was possible to calculate the proportion of manholes with an RPN above the minimum RPN threshold in the highest severity ratings. The category of "highest severity ratings" was the highest severity rating at which there were at least enough manholes to meet the objective function constraint. For example, if the objective is to find 50 manholes with RPN greater than or equal to 50, then the search would begin with the highest possible severity score of 10. If there were more than 50 manholes with RPN greater than or equal to 50, then only manholes with a severity rating of 10 would be considered in the proportion. If there were not enough manholes found, then manholes with a severity rating of 9 would be considered. Similarly, the severity rating would continue to decrease until at least 50 manholes were in the population. In only one case did the population needed to be expanded to severity ratings of 9. Through trial and error, good results were consistently found when the population was 10 times the number of locations being sought.

It was hypothesized that the optimal number of monitors needed in the ESA search was correlated to this proportion of high RPN manholes in locations with high severity rating. The independent variable labelled “Proportion of Locations with High Severity Ratings meeting RPN Criteria” in figure (5-20), is the ratio of the locations with an RPN greater than or equal to 50 which also had severity ratings equal to 10, divided by the total count of locations in the entire system that had severity ratings equal to 10. There was one exception, run #1, where the severity ratings had to be dropped to 9 or greater to have at least 50 monitors in the denominator of the ratio. The dependent variable, shown on the Y-axis of figure (5-19), is the value of the numMonitors parameter in the ESA algorithm that produced the lowest average cost in three replications of the simulation at each treatment.

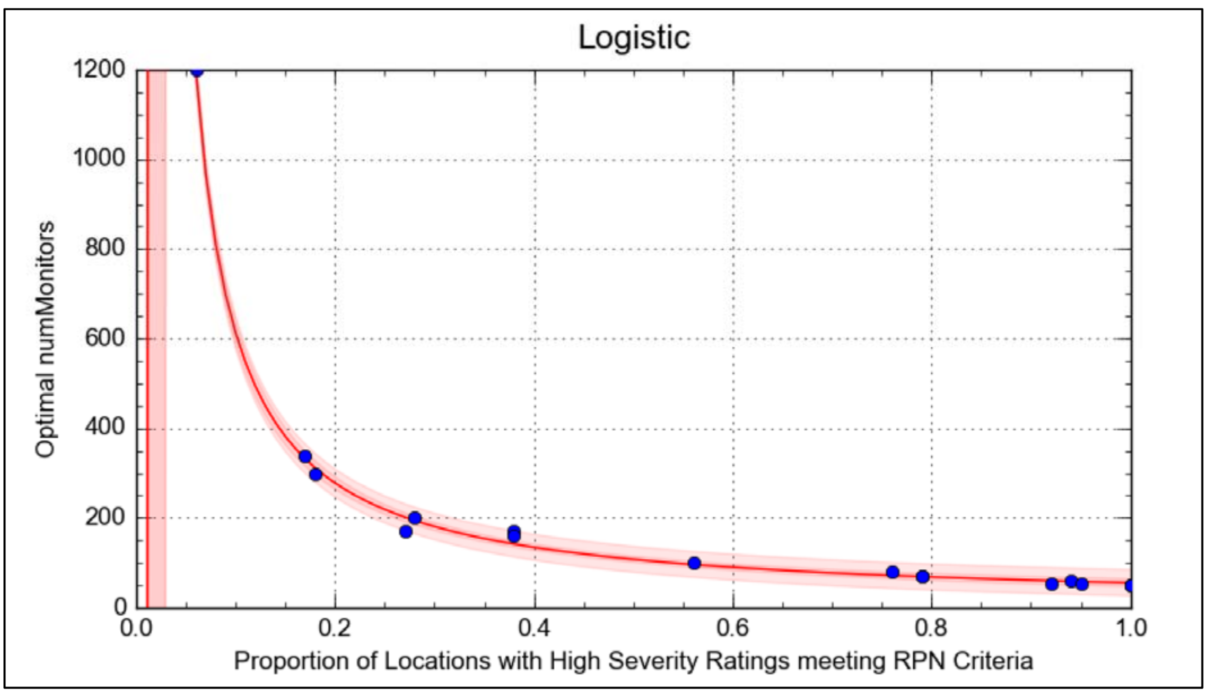

Figure 5-19: Estimation of the proportion of high RPN manholes

A logistic regression model provided a very good fit to the data with a coefficient of determination (r^2) statistic of 0.998. From this model, the optimal numMonitor settings, y, could be predicted by equation (5-1).

$$y = 9.66 / (1 + -1.00 * e^{(-0.195x)}) \qquad (5\text{-}1)$$

5.4.1.3.3 Estimation of the proportion of locations with high severity ratings meeting RPN criteria

In the previous section, the proportion of locations with high severity ratings meeting the RPN criteria was based on the knowledge of RPN numbers for all locations in the collection system. However, in practice, these numbers cannot be known without monitoring every location, which is cost prohibitive. Therefore, an analysis was undertaken to determine how well this proportion could be estimated using the data gathered in a relatively small and rapid monitoring phase, termed the “sampling phase”.

In this sampling phase, the number of monitors deployed should not exceed the number of permanent locations being searched for, due to the possibility that every monitor in the sample be placed in a location that met the RPN criteria. In such a case, the search objectives would be met in this sampling phase without any excessive monitoring. If an insufficient number of locations met the RPN criteria in the sampling phase, then the data would be used to estimate the additional number of monitors to be deployed in the search phase based on equation (5-1). For the purposes of validation, the number of monitors deployed in the sampling phase was 50.

Based on the chosen sample size, the population proportion, and the population size, confidence intervals were constructed for the proportion of locations with severity ratings meeting RPN criteria for each treatment as shown in table (5-11). The confidence intervals were constructed at an 80% confidence level based on the conclusion that it was acceptable to have two out of 10 sample proportions that did not contain the population proportion. It was also noted that the confidence intervals were wide in some instances and could be narrowed by increasing the sample size. Note that 2 additional runs were added to the experiment. Run #0 was added using the optimal parameters settings found for the ESA search algorithm. Run #17 was added using the center points for the designed experiment.

Table 5-11: Confidence intervals for the proportion of locations with severity ratings meeting RPN criteria for each treatment

Run	Confidence	Sample size	Pop Prop	Pop Size	Prop LL	Prop UL
0	80%	50	56%	141	48.70%	63.21%
1	80%	50	6%	377	2.29%	10.58%
2	80%	50	79%	553	72.34%	86.34%
3	80%	50	18%	168	11.90%	23.54%
4	80%	50	92%	556	87.76%	96.96%
5	80%	50	27%	77	22.40%	32.02%
6	80%	50	100%	1,772	100.00%	100.00%
7	80%	50	38%	105	31.38%	44.16%
8	80%	50	100%	1,633	99.25%	100.50%
9	80%	50	94%	447	90.08%	98.13%
10	80%	50	28%	330	20.88%	35.97%
11	80%	50	79%	602	72.28%	86.35%
12	80%	50	17%	143	11.49%	22.51%
13	80%	50	95%	709	91.07%	98.76%
14	80%	50	76%	489	68.58%	83.28%
15	80%	50	100%	1,541	98.66%	100.69%
16	80%	50	38%	104	31.72%	44.47%
17	80%	50	100%	1,907	100.00%	100.00%

5.4.1.3.4 Motivation for a multi-phase search technique

The term “multi-phase search” is used here to describe the methodology with an initial sample phase followed by one or more iterations of the ESA algorithm. The number of monitors employed in each iteration is determined by the estimated proportions of all prior phases using formula (5-1).

Three replications of the multi-phase search were conducted for each of the 17 experiment treatments plus run #0, for a total of 18 combinations of hotspot and coolspot parameters which produced 56 results. From these results, the following observations were deduced:

1. The number of iterations varied depending on the relative scarcity of the locations being sought. In 12 of the 56 results (22%), the required number of locations was found in the sampling phase. These were environments where nearly 100% of the high severity locations met the RPN criteria. In seven results (13%) the search phase consisted of two additional iterations, for a total of three iterations to meet the objective function constraints. These occurred in treatments where the high RPN proportion was low, between 6% and 38% of the population. In no cases were more than 3 total iterations required.
2. In optimal results under the experiment conditions, exactly 50 locations meeting the RPN criteria were found, as finding more than 50 indicated excessive monitoring and associated excessive cost. Figure (5-20) depicts the number of locations found by each run number in the experiment. As seen from the figure, in 20 of the runs, 37%, exactly 50 locations were found. In 87% of the runs, less than 60 locations were found meeting the RPN criteria. In one extreme case, 138 locations were found when seeking only 50. The latter occurred in a case where there was a significant sampling error in the proportion of locations with high severity ratings meeting RPN criteria.

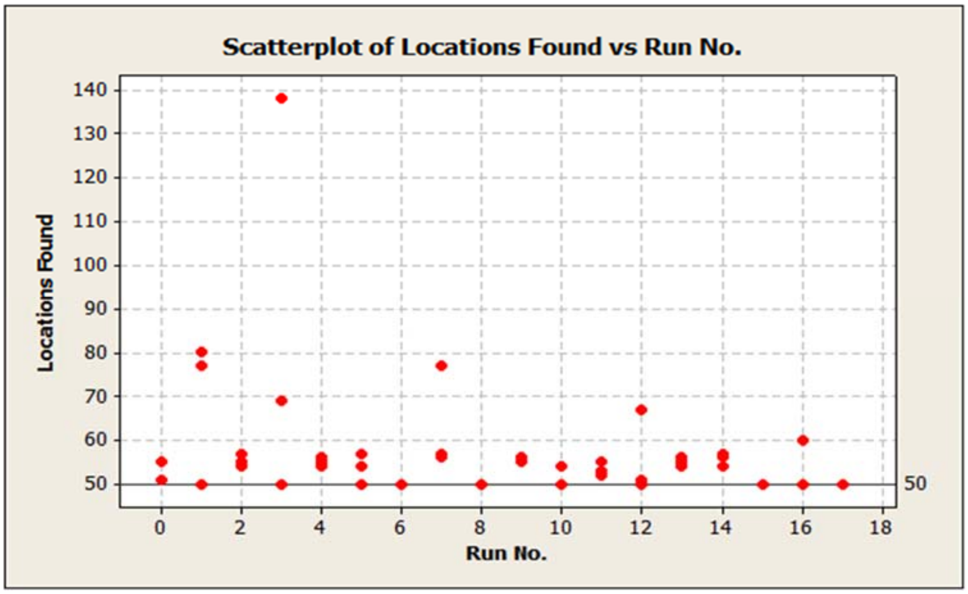

Figure 5-20: Number of locations found by each run number in the experiment

In addition, an important unforeseen benefit of the multi-phase search is that it produced lower average cost compared to the ESA algorithm. The results of a linear regression between the two algorithms in shown in figure (5-21). The lower cost is a benefit from re-estimating the number of monitors needed in successive iterations based on knowledge gained concerning the distribution of RPNs. More precisely, estimating the number of monitors reduces the instances of deploying more monitors than necessary, resulting in needless cost.

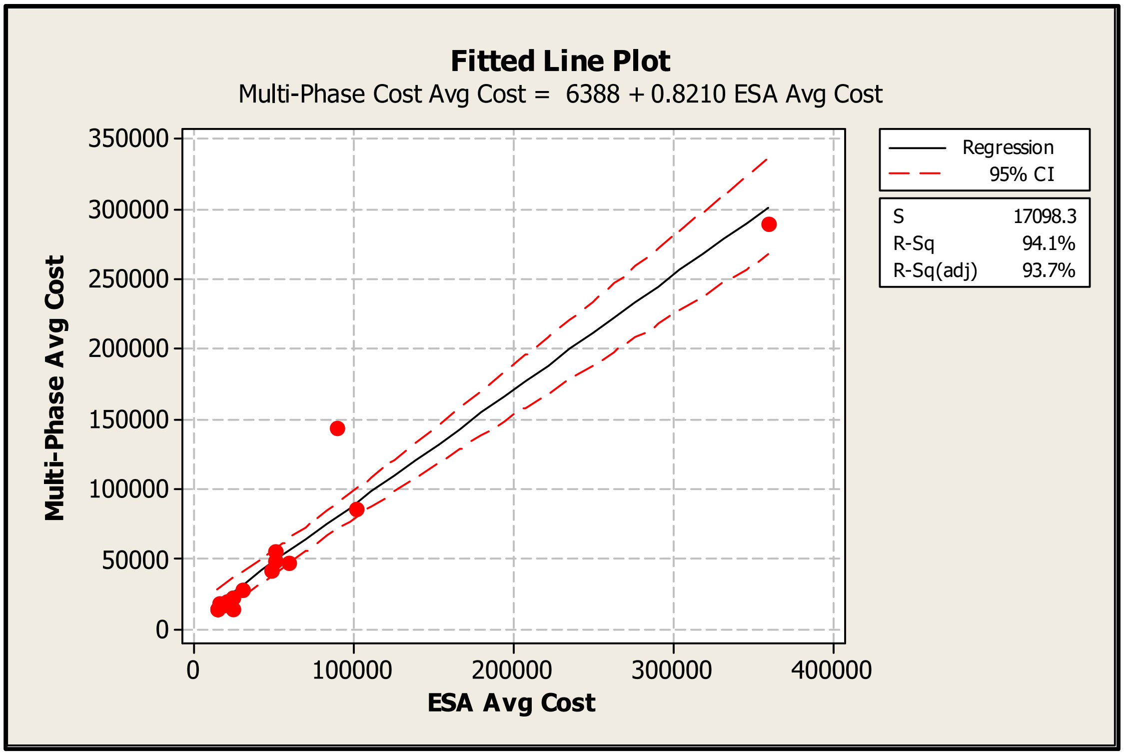

Figure 5-21: Linear regression between the multi-phase search and the ESA algorithm

The formula for estimating the cost of the multi-phase search is shown in equation (5-2)

$$y = 6388 + 0.8210x \tag{5-2}$$

where x is the ESA average cost and y is the multi-phase average cost

Using the default unit cost assumption of \$300/monitor/month, the regression equation predicts that the multi-phase algorithm will produce lower estimated cost when 26 or more monitor-months are required in the search. Monitor-months are the product of the number of monitors and the number of iterations.

The outlier shown in figure (5-21) is run #3, which experienced a replicate that contained a significant sampling error by chance. This is evident from the fact that the regression equation would predict a cost of \$80,278 for run #3, while the costs of the three replicates were $83,400, $106,800, and $243,300, respectively. A probable explanation is that the probability density function for run #3 is unusual, as shown in figure (5-22). From this figure, it is evident that there is a concentration of locations with RPNs between 34 and 40, none of which meet the minimum RPN requirements of the experiment. In addition, the hotspot locations are spread across a large scale, as indicated by the long right tail in the distribution.

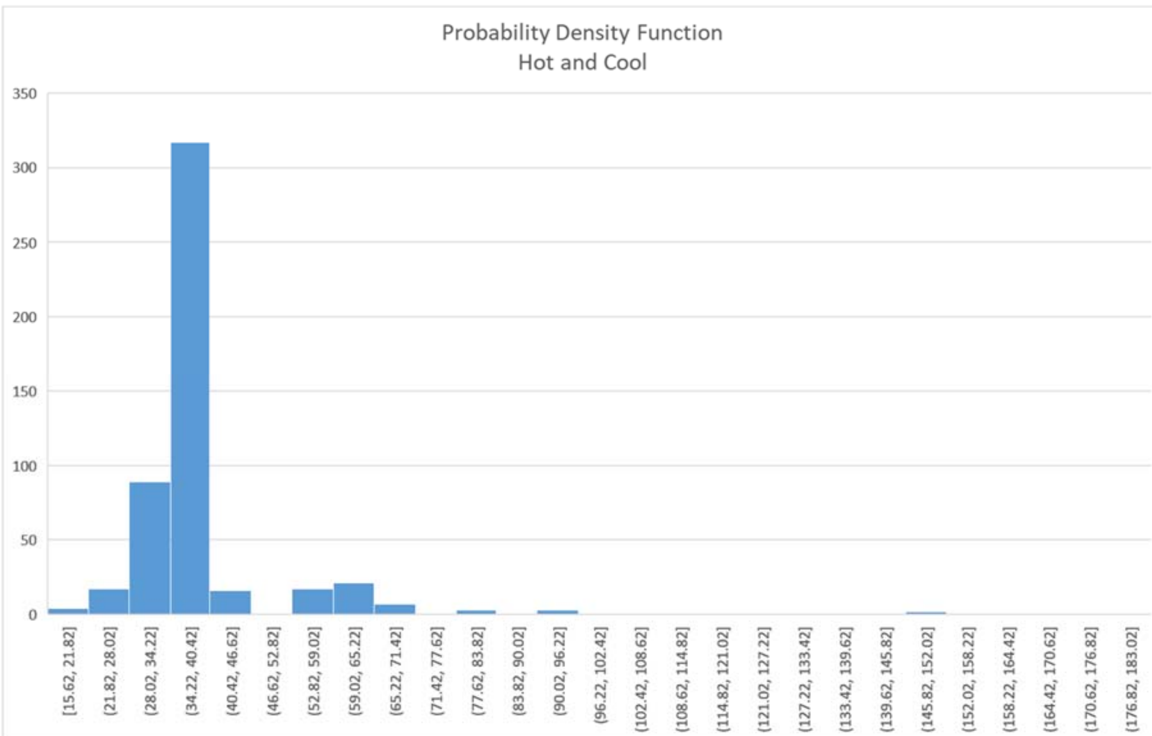

Figure 5-22: The probability density function for run #3

5.4.1.4 Conclusion

In conclusion, as evident from the sensitivity analysis conducted above, the search results are highly sensitive to the differences in the distribution of RPNs. This conclusion resulted in a modification to the search algorithm recommended by this research to incorporate multi-phase search in advance of ESA search.

5.4.2 Sensitivity Analysis for the number of locations and risk threshold

There are two parameters designed into the simulation to reflect the risk preferences of the decision maker - "numPermanentLocations" and "minRPNThreshold". The first of these parameters is the number of locations that the decision-makers determine that can be actively managed according to their risk tolerance and resource constraints. The second parameter is the level of risk that establishes the risk threshold. Since both of these parameters greatly depend on the decision-makers preferences, experiments were conducted with the simulation to assess the sensitivity of the ESA algorithm to such concerns.

5.4.2.1 Experiment design

To understand the sensitivity of the search algorithm to these parameters, a multi-level DOE was undertaken with the two parameters as factors. To improve the resolution of the response, four levels were selected for each factor as shown in table (5-12). Three replicates were run for each of the 16 treatments, for a total of 48 simulation runs.

Table 5-12: The selected levels for each factor

Factor	Level 1	Level 2	Level 3	Level 4	Reasoning
numPermanentLocations	50	200	350	500	Lowest & highest levels programmed in the simulation - 300 is $1m/year monitoring program
minRPNThreshold	30	40	60	70	Vary by 10 to get into different bins. 50 is already evaluated in the optimization runs

The enhanced simulated annealing (ESA) algorithm was utilized for these simulation runs based on its demonstrated effectiveness in finding solutions at a low cost and low monitoring duration. The parameters that were not involved in the experiment were held at the levels found optimal during the optimization experiments. In addition, supplemental runs were undertaken to gauge the sensitivity to the changes in the parameters that were found to be significant in screening experiments with the ESA algorithm. These were the number of agents (“numMonitors”) and the maximum number of nearest manholes an agent could move to in one iteration (“numNearestManholes”).

5.4.2.2 Results

The initial results of the multi-factor experiment showed that only the minRPNThreshold parameter was statistically significant for the average cost of the search. The numPermanentLocations parameter had a p-value of 0.22, which was deemed insignificant at 95% confidence. The r^2 statistic for the linear model was 0.72. These results raised questions that prompted further exploration which indicated that a 2nd order polynomial is a better mathematical relationship of the minRPNThreshold to the cost response with an improved r^2 of 0.72 to 0.91, as shown in figure (5-23).

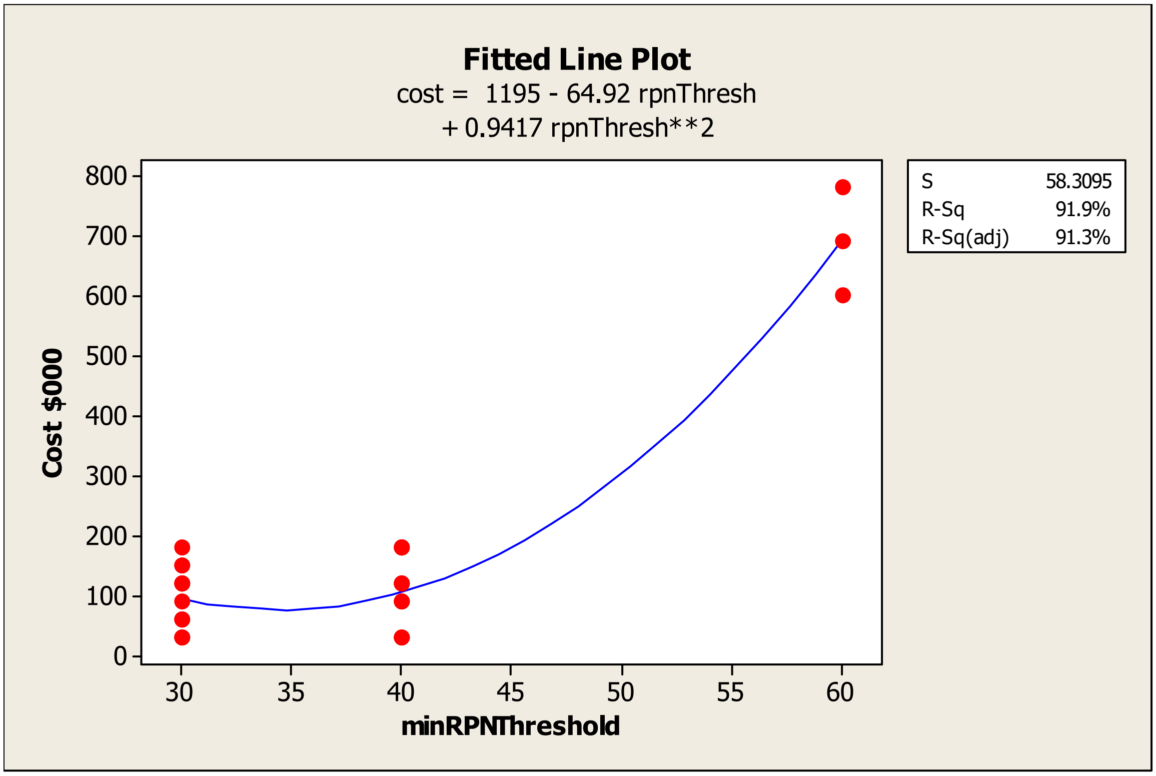

Figure 5-23: The 2nd order polynomial for the relationship between the minRPNThreshold to the cost response

The plot in figure (5-23) illustrates the nature of the cost response. When the minRPNThreshold is set at low levels, the cost is insensitive to changes in the threshold due to the abundance of locations with RPN values above the threshold. There is an inflection point between the threshold values of 45 and 50 where the number of locations above the threshold diminish rapidly. When the threshold is set at these higher RPN values, the cost to find a solution increases as a power function due to the need to monitor many more locations in order to find a sufficient number of locations that meet the criteria.

Further exploration of the residuals of the fit above led to the discovery that outliers at the highest minRPNThreshold of 60 were concealing a linear relationship of the residuals to the numPermanentLocations parameter as is shown in figure (5-24).

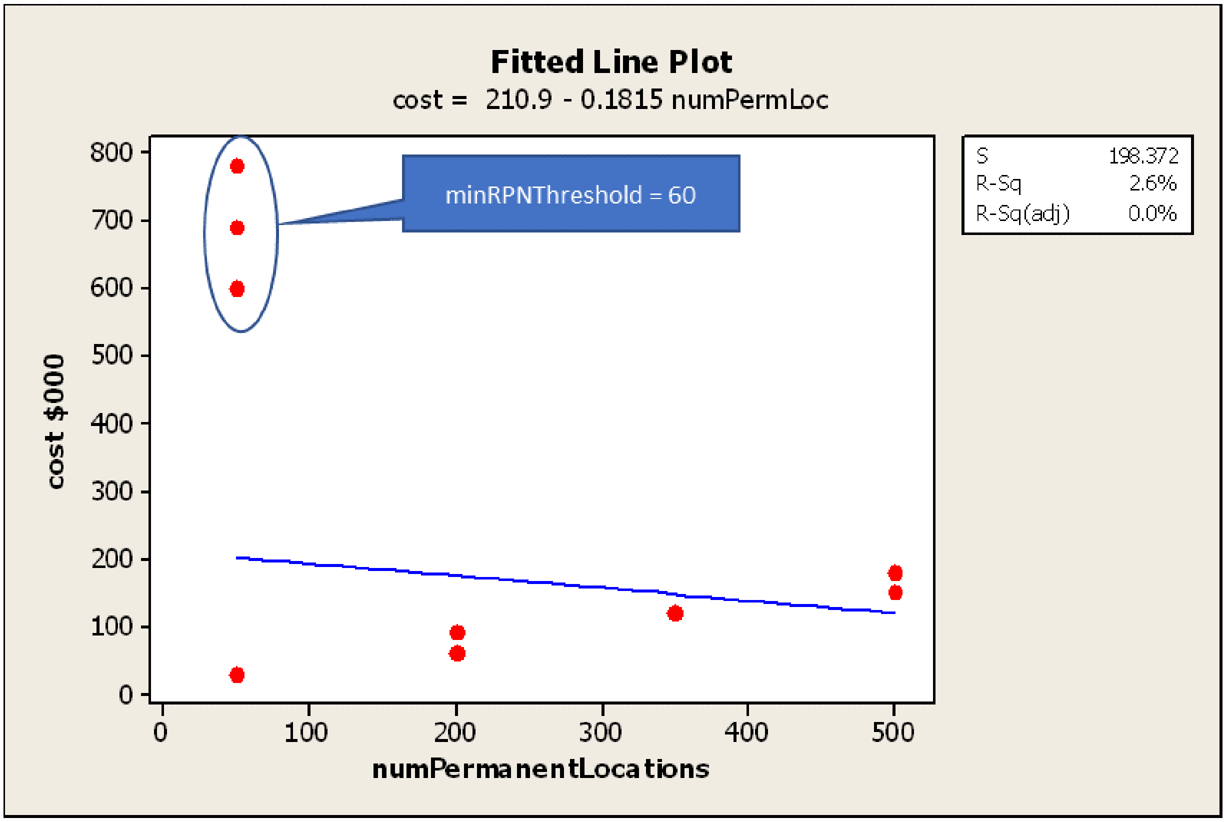

Figure 5-24: Residuals of the fit

To overcome this problem, the outliers were removed, and a new regression analysis was conducted for the lower threshold values, as shown in figure (5-25). This was performed with the understanding that there exists a minRPNThreshold value which, once exceeded, would relegate the effect of numPermanentLocations to noise. It is also noted that at very high settings for numPermanentLocations, a solution was not found before the simulation termination conditions were met. There were no solutions when the minRPNThreshold was at 60 and numPermanentLocations was 200 and higher. Similarly, when the minRPNThreshold was set at 70, no solution was found due to the lack of manholes in the population that had RPN values above the threshold.

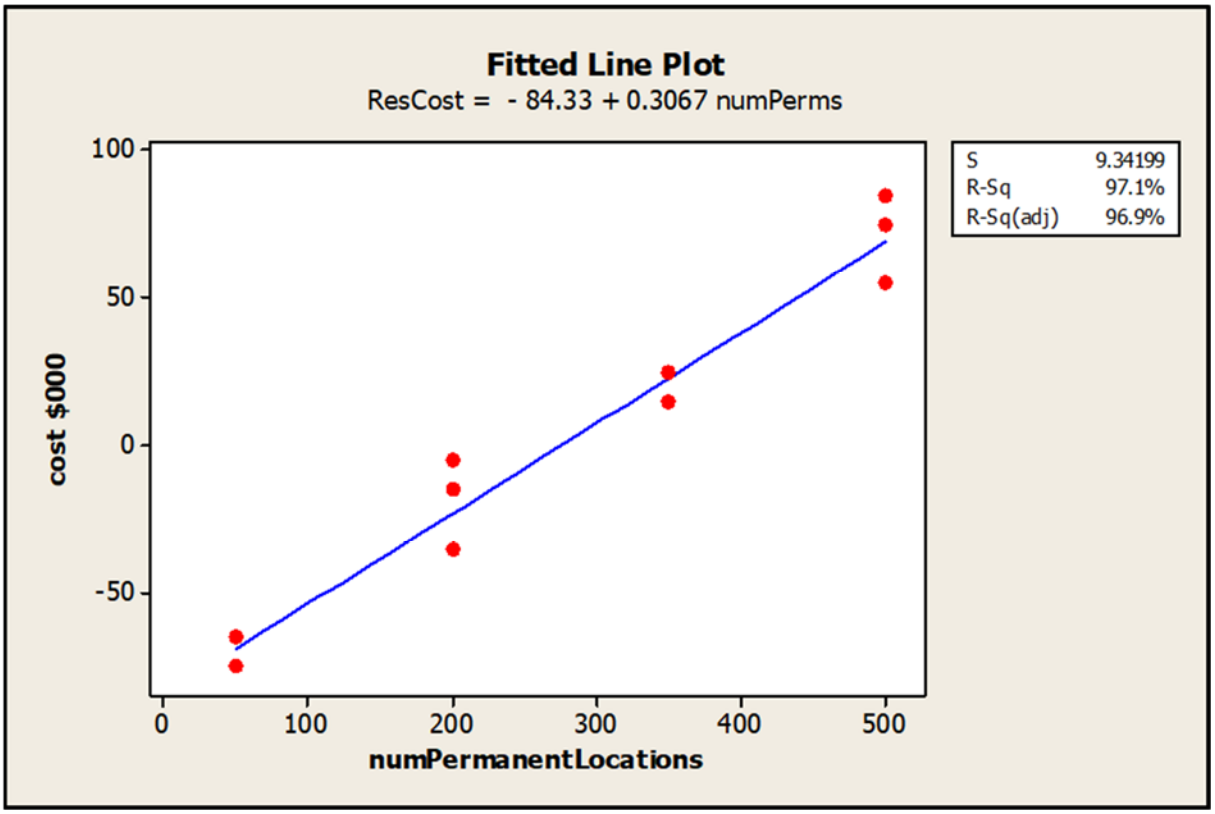

Figure 5-25: The fitted line plot for the lower threshold values

By combining the fit of response values and that of the residuals, the following prediction equation is formulated:

$$\text{Estimated search cost} = 1110.67 - 64.92(\text{minRPNThreshold}) + 0.9417(\text{minRPNThreshold})^2 + 0.3067(\text{numPermanentLocations}) \quad (5\text{-}3)$$

As shown in figure (5-26), adding the numPermanentLocations term improved the r^2 statistic from 0.91 to 0.99 which held true for all values of minRPNThreshold below 60.

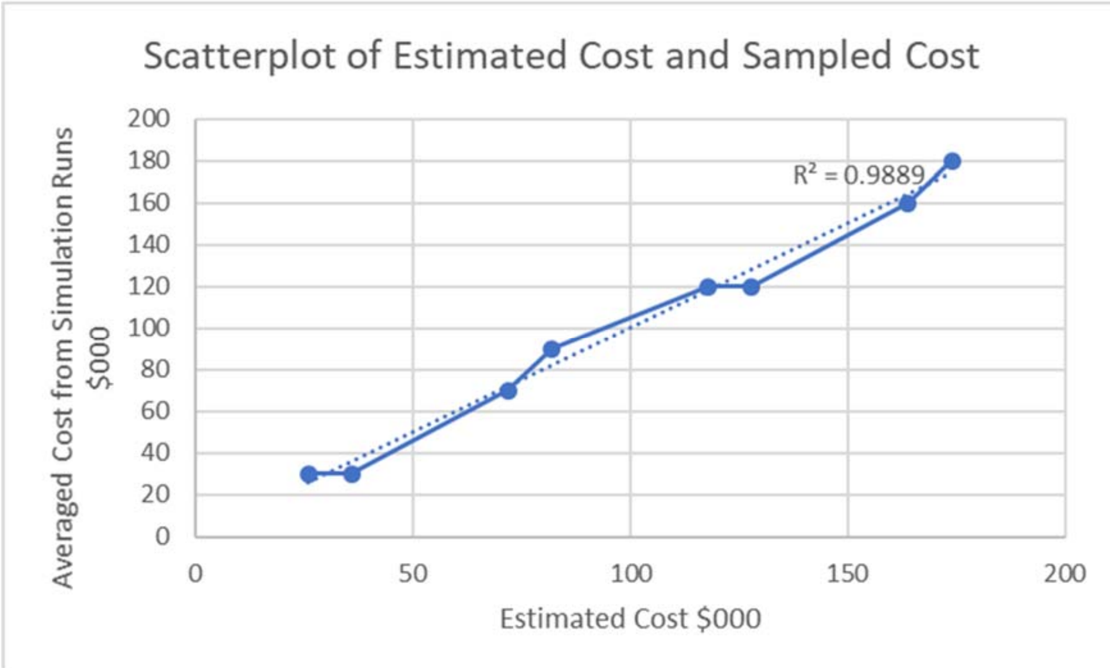

Figure 5-26: Scatterplot of estimated and sampled costs

5.4.2.3 Optimal numNearestManholes parameter settings under varying minRPNThreshold values

As the minRPNThreshold values changed, it might also be beneficial to increase or decrease the agent movement restrictions which are controlled by the vector of numNearestManholes parameters. There are nine values in the vector corresponding to RPN ranges 1-10, 10-20…etc. Experiments in finding the optimal parameter settings for the ESA algorithm suggested that only the setting in the “critical bin”, defined as the value of the numNearestManholes parameter that contains the minRPNThreshold value, produced a statistically significant effect. Therefore, a 10-factor 2-level experiment with three replicates was designed to gain insight into this question. This is shown in table (5-13).

Table 5-13: The 10-factor levels used in the experiment

Factor	Low	High	Reasoning
minRPNThreshold	30	60	Range covered by the simulations in the experiments
numNearestManholes 1	130	500	This range produced response in ESA optimization experiments
numNearestManholes 2	130	500	
numNearestManholes 3	130	500	
numNearestManholes 4	130	500	
numNearestManholes 5	130	500	
numNearestManholes 6	130	500	
numNearestManholes 7	130	500	
numNearestManholes 8	130	500	
numNearestManholes 9	130	500	

The numPermanentLocations parameter was held at a value of 50 because it had shown to give a range of outcomes, while the numMonitors parameter was held at 40 after preliminary simulation runs demonstrated that it produced several multi-iterations runs. It was suspected that some features of the metaheuristic search were more evident in multi-iteration runs than those that reached a solution on the initial placement of monitors. It was also known that the multi-phase approach commonly required three iterations. In addition, the coolingRate parameter was held at a value of 5 which was lower than in the ESA optimization experiments because the lower temperature allowed the simulation to perform more iterations before hitting its stopping criteria. A large number of iterations were needed to find a solution when the minRPNThreshold values were high.

Similar to previous experiments, the results showed a strong linear relationship between minRPNThreshold values and the cost response. The effect of the critical bin values was statistically significant but much smaller in practical significance. This is also true of the interaction between the two factors. None of the other numNearestManholes factors was statistically significant. Figure (5-27) shows the results of this experiment.

Factorial Fit: cost versus minRPNThreshold, numNearestManholes6

Estimated Effects and Coefficients for cost (coded units)

Term	Effect	Coef	SE Coef	T	P
Constant		307.6	8.545	36.00	0.000
minRPNThreshold	567.3	283.6	8.545	33.19	0.000
numNearestManholes6	83.7	41.9	8.545	4.90	0.000
minRPNThreshold*numNearestManholes6	83.8	41.9	8.545	4.90	0.000
Ct Pt	-283.6	49.086	-5.78	0.000	

S = 83.7210   PRESS = 717404

R-Sq = 92.64%   R-Sq(pred) = 91.99%   R-Sq(adj) = 92.33%

Figure 5-27: Results of the optimal numNearestManholes parameter settings

Based on the above experiment, additional observations were evident. First, it was observed that when minRPNThreshold values were at 45 or below, the solution was always found in two iterations. When this occurred the numNearestManholes setting was irrelevant. This was later found to be exactly as expected given the proportion of locations with RPN values above 45. Second, when the number of iterations was high, as in the case when minRPNThreshold was greater than or equal to 60, the numNearestManholes value appeared more influential. Lower values of numNearestManholes produced better results in those situations. This can be explained by the fact that there were many more agent movements involved in the solution. An example of this relationship is shown in interval plot in figure (5-28), where two levels of the minRPNThreshold are shown with varying numNearestManholes6 values. From this figure, at the threshold value of 55 there is little difference in cost. In contrast, at the threshold value of 60, the costs are significantly higher, and the variation is higher between numNearestManholes6 settings.

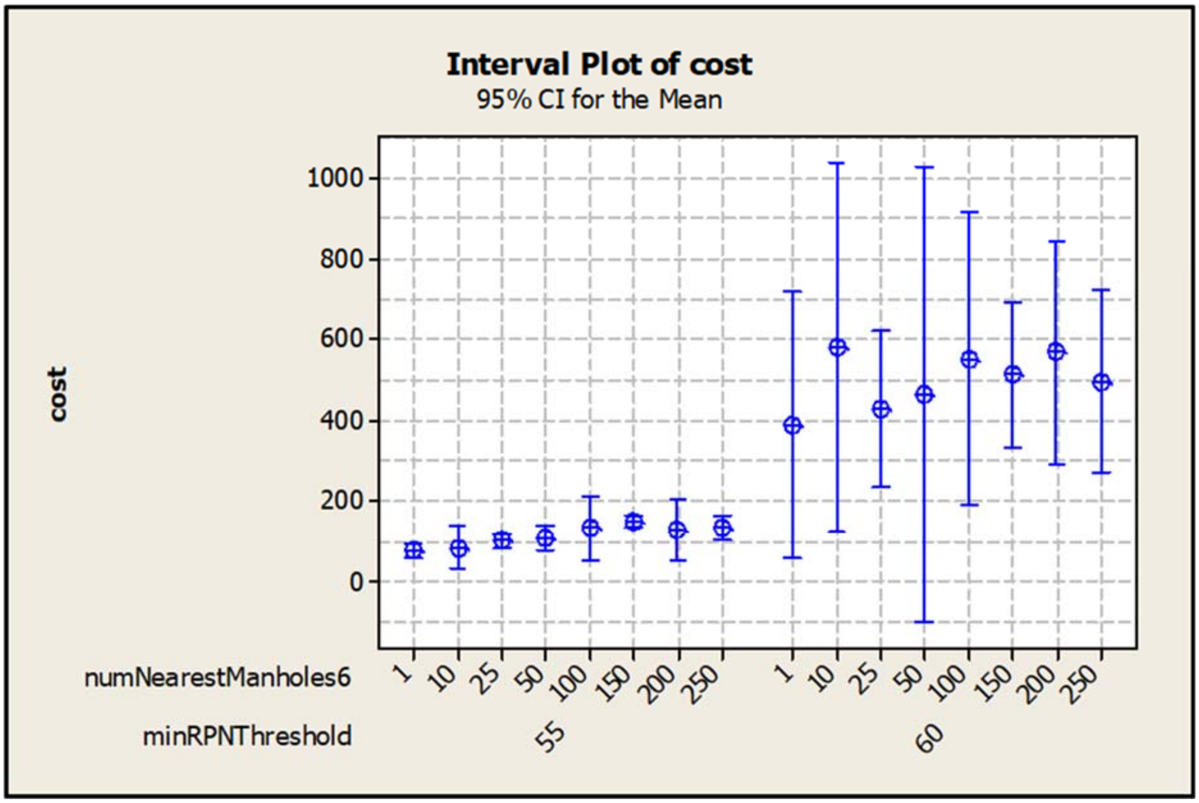

Figure 5-28: Example of the influence of the values of numNearestManholes

Another valuable observation is the performance of the ESA algorithm in the presence of changing RPN threshold values. At higher thresholds, the number of iterations required to find a solution increases due to the scarcity of locations that exceed the threshold. Comparing the number of iterations it took in experiments to find a solution versus the expected number of iterations based on the proportion of manholes meeting the threshold condition is a measure of the efficiency of the ESA algorithm. This proportion is further stratified by the severity ratings because the ESA algorithm begins with the highest severity ratings and progressively reduces them until a solution is reached. This comparison is presented in table (5-14) and figure (5-29). Note that in the case of RPN thresholds of 55 and 60, the severity rating in the search population was reduced from 10 to 9 so that the search population contained enough manholes to reach the objective of 50 locations discovered with 40 agents.

Table 5-14: Experimental versus expected number of iterations

minRPNThreshold	Number of qualifying locations in the pop./count in the population	Proportion of qualifying locations in the population	Expected number of iterations based on proportion of qualifying manholes in the population	Average number of iterations required by the ESA algorithm in experiments
30	250/252	99%	2	2
45	190/252	75%	2	2
49	156/252	62%	3	3
50	141/252	56%	3	3
55	596/6557*	9%	14	10
60	150/6557*	2%	55	47

*Population includes all locations with severity code of 9 and 10

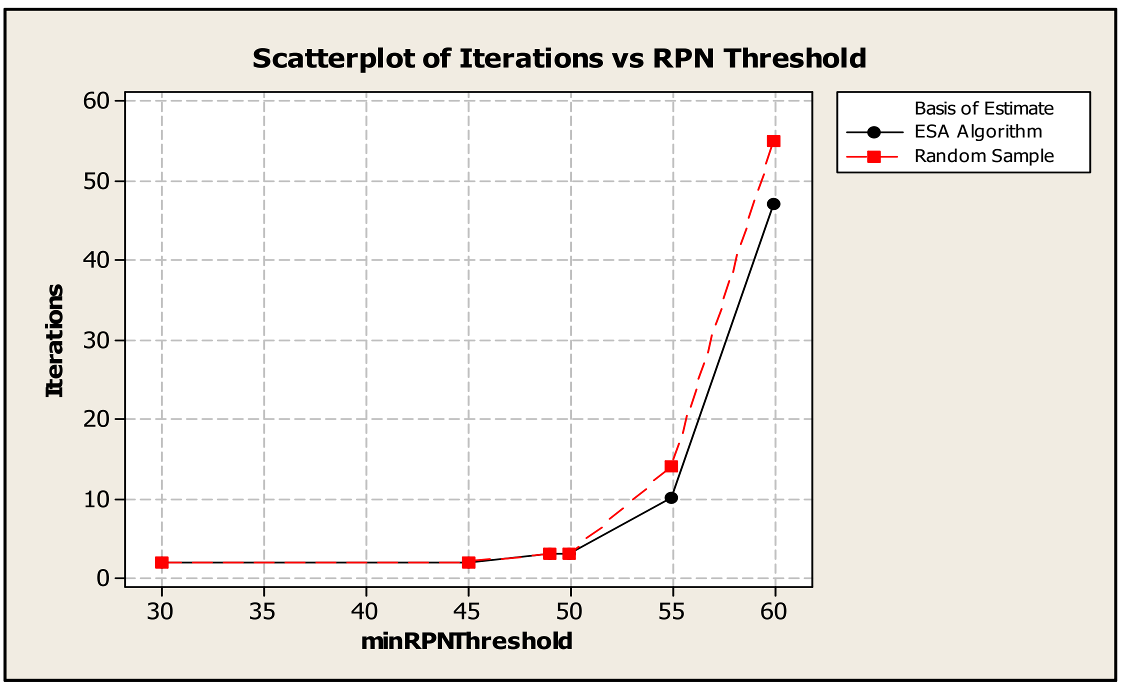

Figure 5-29: Experimental versus expected number of iterations

As seen from the figure, with higher iterations the ESA algorithm is more efficient than random search. It is evident from the above table that the proportion of qualifying manholes in the population decreases dramatically between threshold values of 50 and 55, and this is where the inflection in cost occurs. This observation is a further support for the multi-phase approach where the number of iterations is expected to be three or less. In that situation, knowledge of the actual distribution of clusters is not a significant deterrent to the cost of finding a solution.

The results of this testing were inconclusive for determining the optimal setting of the numNearestManholes setting at the critical bin. In general, smaller values of numNearestManholes in the critical bin produced lower averaged cost. However, at very small movements, there is a possibility of a single failure event being registered by several of the closest manholes in the area if they are on the same line. Therefore, the values of 1 and 10 were rejected. A value of 25 for numNearestManholes at the critical bin was considered a good compromise, keeping in mind that when applying the multi-phase search technique, the number of iterations is likely to be three or less and therefore the numNearestManholes setting would be inconsequential.

5.4.3 Sensitivity analysis for the number of known hotspots

In this section, experiments were undertaken to assess the impact of estimating the number of known hotspots in lowering the cost of achieving the search objective.

5.4.3.1 Experiment design

A two-factor, four-level DOE was created for the purpose of determining if the number of known hotspots affected the cost of the search. The parameter “knownHotspots” was used in the simulation to allow the user to enter an integer between zero and the numMonitors parameter value. When a non-zero number is entered, the initial placement of that number of monitors is a random manhole within the boundaries of randomly chosen hotspots. For this experiment, the ESA algorithm was utilized with the parameters that were found to be optimal in the optimization experiments described earlier. During the experiment, the two factors that were varied were the knownHotspots parameter and the numMonitors parameters. The numMonitors parameter was varied because it was found to have the highest impact on the cost outcome in the optimization experiments and it was suspected that there would be 2-way interactions between these two factors. The levels chosen for the factors are shown in table (5-15). The experiment was full factorial with three replicates of each treatment that resulted in a total of 48 simulation runs.

Table 5-15: The selected levels for each factor

Factor	Level 1	Level 2	Level 3	Level 4	Reasoning
numMonitors	85	90	95	100	These were in the range of the observed monitors with varying knownHotspots
knownHotspots	0	9	18	28	Full range from zero to 100%

5.4.3.2 Results

The regression results indicated that higher numbers of knownHotspots did result in lower costs, while the numMonitors parameter was not statistically significant in the linear model. The scatterplot below, figure (5-30), provides some visibility into a non-linear response. As observed from the figure, when the constraints of the objective function were met in a single iteration, there is a clear linear response, as indicated by the black dots. There is also a linear response when two iterations are required, as indicated by the red dots.

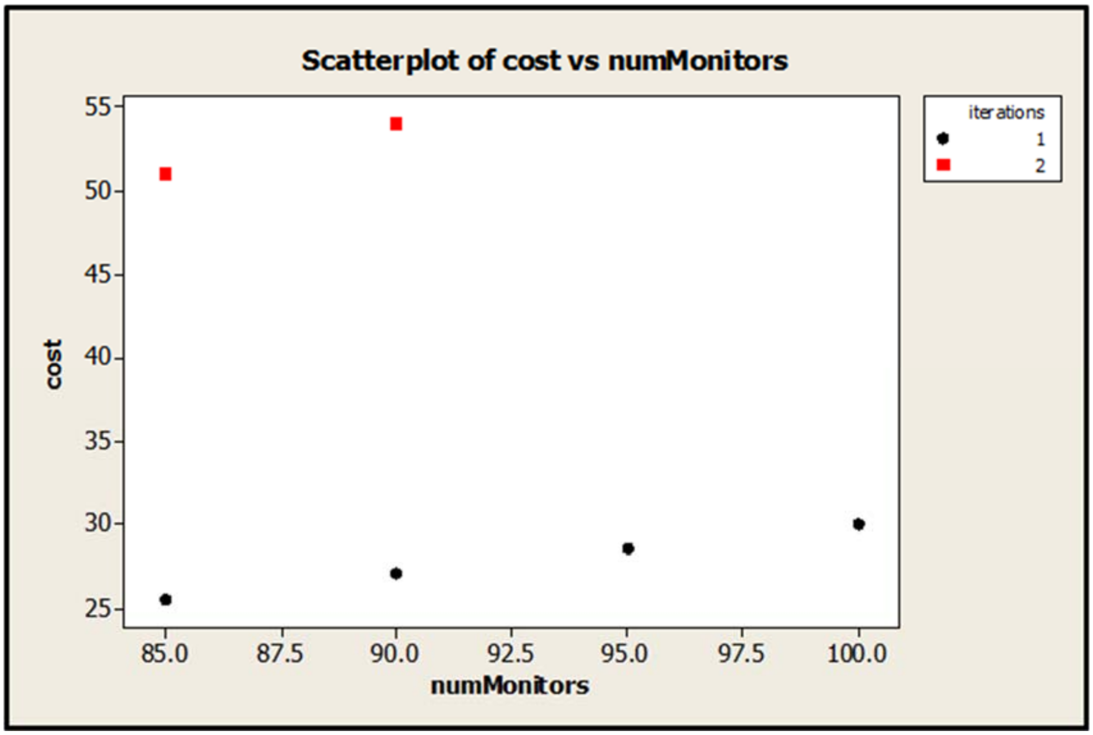

Figure 5-30: Scatterplot of the numMonitors parameter

Further exploration revealed that the number of iterations was a function of knownHotspot and numMonitor levels as shown in figure (5-31). Note that the "UC" designation in the axis titles indicates uncoded values of the factors.

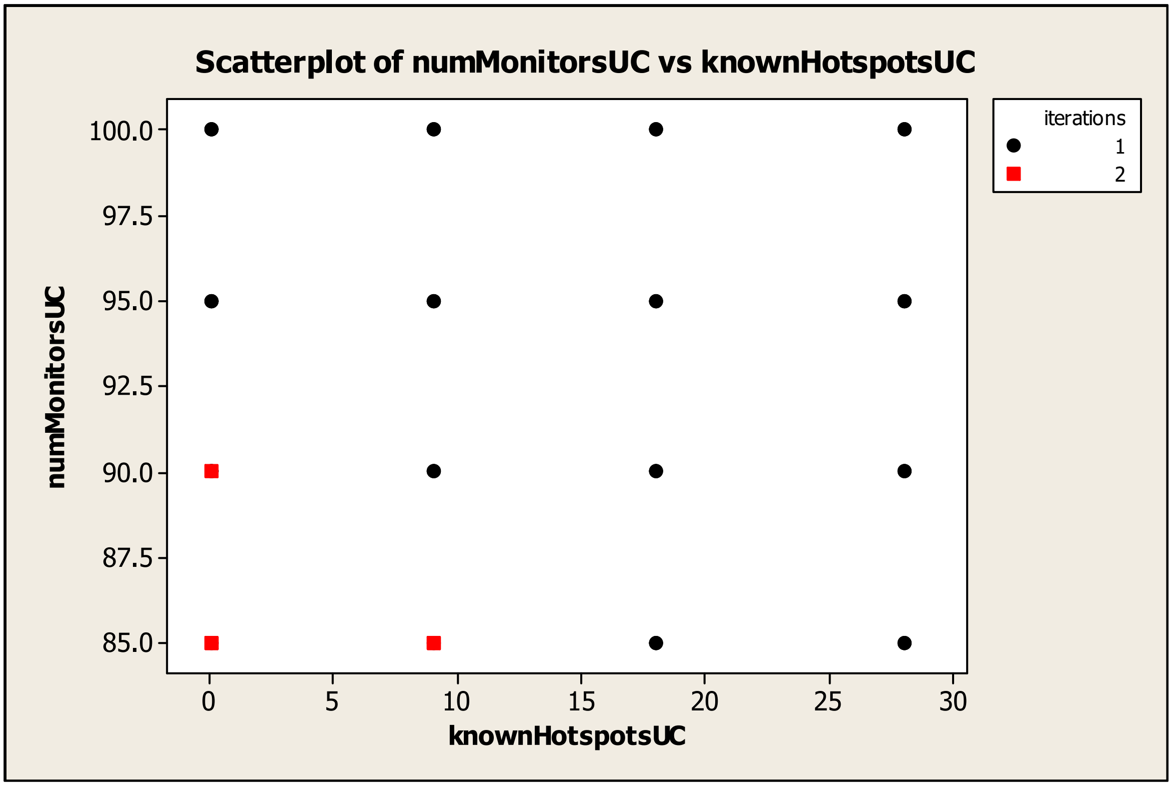

Figure 5-31: Scatterplot of the knownHotspots parameter

From these two figures, it can be concluded that as the number of knownHotspots increases, the number of iterations, and, consequently, the cost of the search, will decrease.

5.4.3.3 Application of the number of known hotspots in the multi-phase approach

In order to assess how to apply the knowledge of known hotspots and what is the expected benefit, further analysis was conducted in a sample of differing RPN distribution scenarios. Because the full range of RPN distributions that might be encountered is not known, the purpose of this analysis was only to determine if there could be a benefit to utilizing knowledge of known hotspots and whether it might be of sufficient benefit to warrant the additional expenses of analyzing historical records and interviewing system operators to estimate the location of hotspots.

From the experiments of varying RPN distributions, three experimental runs were selected. Run #15 which produced a consistent 1-iteration solution, run #11 which produced a consistent 2-iteration solution, and run #10 which produced a consistent 3-iteration solution. For each of these three runs, three replications were performed. To conduct this analysis, a modification was made to the simulation to tag all locations either in a labelled hotspot or in no hotspot. The log files of each run were then consolidated into a single database. Next, the proportion of locations above the threshold value of 50 were compared between the population of all monitors and the population of only monitors within hotspots. Because the ESA algorithm begins its search with severity codes of 10 and moves to successively lower severities, the data was stratified based on severity code.

The results of this analysis are shown in figure (5-32) from which three observations were made:

1. When the proportion of qualifying manholes is close to 1, there is no difference in the outcome between seeding agents within hotspots or not. This is intuitive as one would expect nearly every monitor to be assigned initially to a location with an RPN which exceeds that threshold.
2. When the candidate manhole population were the ones with a severity code of 10, it is preferable to assign at least some agents to the known hotspots. In the case of run #10, the hotspot locations had a significantly higher proportion of qualifying manholes than the total manhole population with severity equal to 10. In run #15, the difference was not statistically significant.

3. When the candidate manhole population were the ones with a severity code of 9 or greater, the results vary. This is believed to be dependent on the distribution of high RPN manholes within hotspots. The RPN distribution of run #15 is expected to be unusual as, in that run, the location parameter of the hotspots is less than that of coolspots. On the other hand, run #10 is expected to be more typical as it produced the expected result of a benefit to placing agents within known hot spots.

Figure (5-32) provides information on the magnitude of the cost savings through utilizing the known hotspots. As seen, the difference can be potentially worth the expense of gathering additional data as long as the proportion of qualifying manholes is not close to 1.

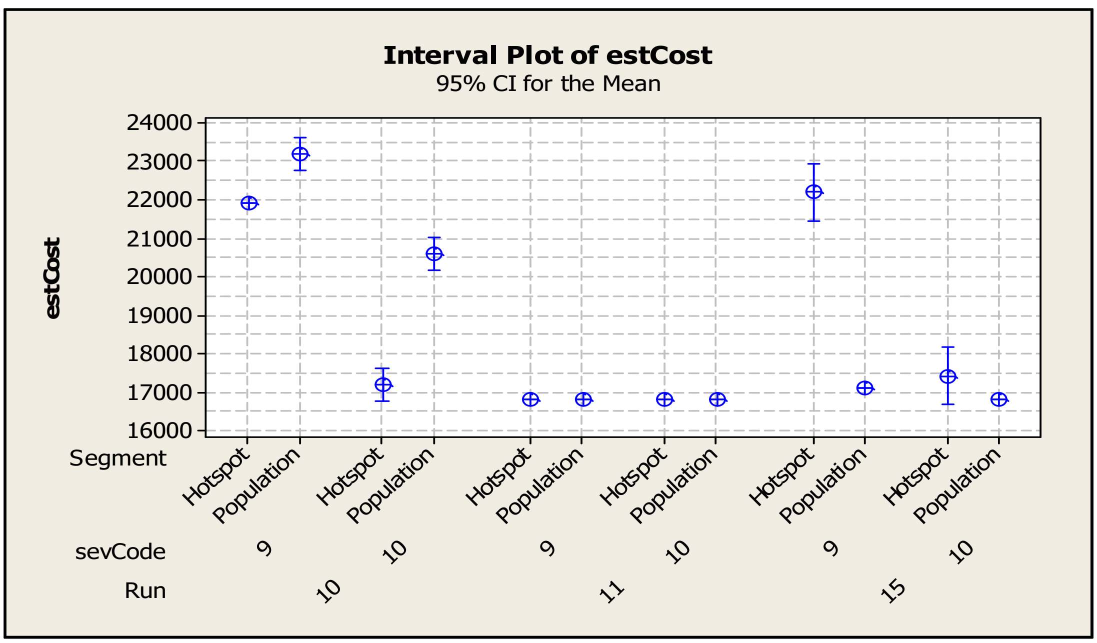

Figure 5-32: Results of the application of the number of known hotspots in the multi-phase approach

These results raise questions for the implementation of the multi-phase approach. The first is whether all monitors should be placed within the hotspots to gain their potential benefit of a higher proportion of qualifying manholes. The risk of this approach is that it assumes true knowledge of hotspots based on observations, usually pipe failures that caused surface flooding, which can be misleading and lead to the placement of monitors in areas that are not truly hotspots. Moreover, this approach ignores the possibility of unknown hotspots that could be discovered in the course of the search. In addition, a second risk of placing all monitors within the known hotspots is that multiple monitors will detect the same failure mechanism. For example, a blockage within a pipeline can cause elevated water level measurements for many manholes upstream. If multiple monitors are placed along such a pipeline, several may assign occurrence codes based on elevated d/D levels caused by the same blockage. This will incur the opportunity cost of not placing the redundant monitors in new locations where independent risks are present.

Based on the above, a compromise solution is recommended until more research results are available. It is recommended that a single monitor be placed initially within each known hotspot as long as it complies with the severity code criteria of the ESA algorithm. Furthermore, other available monitors should be placed randomly within the system based on severity codes. Although this approach may not take full advantage of the density of high-risk manholes within hotspots, it hedges against the possibility of unknown hotspots and multiple monitors detecting a single failure mechanism.

CONCLUSIONS AND FUTURE RESEARCH

6.1 Conclusions

This research developed a framework for managing the risk of failures in sewers due to maintenance issues. In the course of the research, a number of advances and developments in the state-of-the-art in research and practice were achieved. These include: 1) Establishment of an encompassing risk management framework for the threat of inadequate capacity in complex infrastructure networks, 2) Validation that a strategy of iterative sensor movements can efficiently assess risks of failures in wastewater collection systems, 3) Development of a method of estimating pipe failure probabilities with limited water level data, 4) Development of a method of directing the allocation and movement of sensors within the sewage network using a metaheuristic search algorithm in multiple phases, 5) Development of a tool to aid in designing and testing risk management strategies for infrastructure networks through agent-based simulation, and 6) Identification of well-defined future research opportunities.

6.1.1 Establishment of a risk management framework

In this research a risk management framework was developed through the adoption of FMEA with adaptations as described in section 4.1.3. This framework is graphically depicted in figure (6-1).

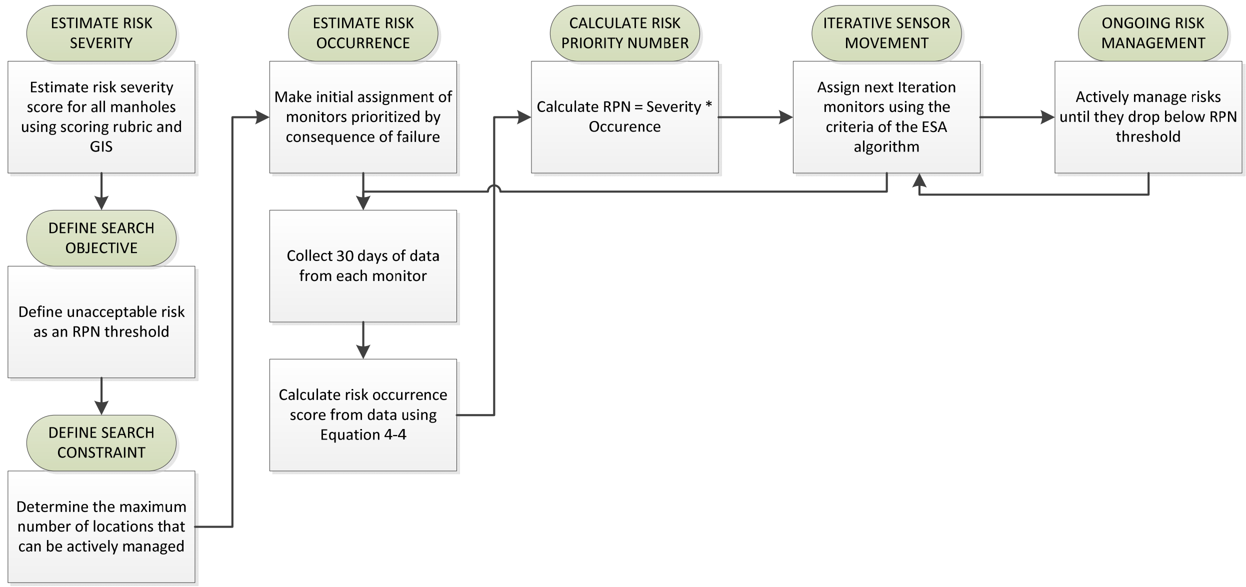

Figure 6-1: Risk Management Framework

A major limitation of previous FMEA applications was the lack of a method for scoring occurrence risk. This research presents a solution to this problem using roving level monitors and a novel analytical process. FMEA was shown to be a valuable construct for integrating the elements of the standard risk model into a practical decision support tool. Eliminating the detectability element of the Risk Priority Number scheme reduced the required inputs to severity scores and occurrence scores. Moreover, a risk priority number, combining risk consequences and risk probability, produced a single measure for ranking the risk associated with locations and the associated establishment of a single value for a threshold. The risk priority number concept allowed the enhanced simulation annealing algorithm to take advantage of the knowledge of severity ratings for the entire search space. In addition, the risk management framework proposed in this research integrates well with GIS, allowing the use of mapping tools in the risk determination process. As a result, this process addresses the seven key elements of risk management as prescribed by the INCOSE Systems Engineering handbook: First, a framework is started by analyzing the risk severity. Second, the analysis of risk likelihood is then accomplished by the iterative movement of sensors guided by the ESA, a metaheuristic search algorithm inspired by simulated annealing. Third, RPN is used to address three of the INCOSE elements by quantifying the risk in a methodical way, allowing for the prioritization of risks by classifying then as either acceptable or unacceptable, and comparing the discovered RPN values with the decision makers RPN threshold. The proposed framework also provides a plan of action for unacceptable risk. When a risk reducing action is taken, the framework provides a way to assess its impact and determine if it is sufficient improvement to make the risk acceptable. If it is, the framework prescribes the next steps of efficiently searching for another location with unacceptable risk. Finally, the framework uses measurements and statistics to help manage risks.

6.1.2 Validation of iterative sensor movements in assessing risk

Another major contribution of this research study is its ability to assess the risk in wastewater collection systems efficiently. This research concluded that the use of level monitors was an effective method to detect pipes at risk of failure before those failures occur. The argument is made that dynamic measures of pipe capacity, such as level data over time, are preferable to a static visual inspection from methods like CCTV inspection. The novelty of this research relative to continuous monitoring is two-fold: The first is that there is value in placing monitors in locations outside of known hotspots. The search algorithms proposed in this research demonstrated that monitors can find high risk locations which were previously unknown. Discovering these locations prior to observed failures will allow system operators to perform preventative maintenance. The second novelty is the value of sensor movement. No prior research has proposed combining search algorithms with continuous monitoring devices. Yet, as demonstrated in this study, moving sensors in accordance with ESA search rules can find a specified number of unacceptably risky locations at $1/7^{th}$ of the cost of sequential search. This benefit is multiplied when comparing the amount of information provided in 30 days of monitoring to an instantaneous visual inspection. For example, 30 days of monitoring using a 5-minute sample rate produces 8,640 measurements of pipe capacity.

6.1.3 Development of a method to estimate pipe failure probabilities

The third contribution is estimating the pipe failure probability with limited data. Prior research and practice have not addressed the question of a single metric of risk probability in terms of free hydraulic capacity. However, the methodology proposed in this research was able to estimate failures with 80% accuracy using only 30 days of monitor data. Moreover, this research study provided insight into the critical importance to the number of sensor measurements showing water levels at the 0.7 d/D bin. The period of 30 days is valuable in that it is a sufficiently short period to be economical and to allow reasonable monitoring durations to converge on a solution. By using the process shown in this study, the desired number of high-risk locations was discovered in no more than three months of monitoring.

6.1.4 Demonstration of the value of metaheuristic search

With regards to the fourth contribution, this research argues that metaheuristic search is an appropriate methodology for approaching problems with this structure. The unknowns surrounding the shape of the search space combined with the cost of acquiring this knowledge motivated the need for trajectory method solutions. In addition, metaheuristic search, in contrast to statistical modeling, requires no knowledge of cause and effect, nor correlations to failures. It was only sufficient to establish that failures cluster and that the search technique employed could take advantage of spatial autocorrelation. To reach this conclusion, a considerable amount of the research time was devoted to the study the various search algorithms with various parameters. The search was guided by an objective function which recognizes that a satisficing goal of finding a pre-determined number of locations at a lowest cost is more practical than an objective function focused on the absolute minimization of risk. Experiments showed that the absolute lowest cost can be achieved by utilizing a single monitor guided by a simulated annealing algorithm using distances as the neighborhood function. This was aided by a low cooling rate parameter, which allowed an extensive freedom of movement in early iterations, with a small neighborhood movement function once high-risk locations were found. These settings best exploited the characteristics of failure clustering by restricting movements to small areas once a hotspot was discovered.

6.1.5 The introduction of multiple phases of search with varying agents

A multi-phase search technique prioritized by location severity ratings and inspired by the ESA algorithm was the most robust search technique of those examined. It yielded the best results in terms of cost and search duration across a wide range of risk distributions. A few important discoveries led to this conclusion:

1. Single-iteration solutions provided the fastest possible solutions and were relatively economical.
2. The single-iteration solutions with the lowest costs were those that used a minimum number of monitors that consistently met the objective function

in a single 30-day monitoring period. Subsequent experimentation showed that this number of monitors was highly dependent on the unknown distribution of risk in the system and the RPN threshold selected.

3. Due to this dependency, simulation demonstrated that a first stage sampling of the search space could provide valuable input to estimate the number of monitors that could provide a single-iteration solution.
4. Experimentation with the ESA algorithm showed the value of limiting the search space by the severity ratings and progressively expanding the search space to lower severity ratings as the search progressed.
5. Combining a first stage sampling with a search space restricted on severity ratings produced a search algorithm that was successful in coping with a range of possible risk distribution scenarios.

The results of the comparisons showed that this multi-phase search technique produced a lower cost than the optimized ESA algorithm whenever 26 monitor months or more of data were required to meet the objective function. In medium to large sewer systems it is almost a certainty that this much data would be prescribed. An unexpected advantage of the recommended search technique is its simplicity. It was found that it is difficult to explain the concepts behind simulated annealing to wastewater system operators in a way that was instinctively appealing. The concept of sampling within the areas of highest failure consequence has been more appealing to those unfamiliar with this topic.

6.1.6 Development of an agent-based simulation tool

It was shown through this research that agent-based simulation is an effective tool for designing and testing risk management strategies for infrastructure networks. A realistic simulated environment was required to enable this research. Agent-based simulation was shown to be well adapted to the problem structure, with dynamic agents representing monitor devices and static agents representing the search space of potential monitoring locations. No prior research was found that employed simulation to model risk propagation in complex infrastructure networks. In the case of sewers, hydraulic models are often used to model drainage networks. However, hydraulic models lack features to address a variety of risk environments and the inclusion of various search techniques to discover potential failures.

Simulation calibration was an important step in providing validation of the simulated environment. The use of the Moran's i, normalized to manhole density, as a statistic for spatial autocorrelation, along with a heuristic to estimate the number of hotspot locations, allowed the calibration of the simulation to the available data.

6.2 Well-defined future research opportunities

Another noteworthy result of this study is the discovery of a few well-defined specific opportunities for future research. In this way, it is hoped that the insights discovered in this research will serve as a launching point for further improvement of methods of managing the risk of failure in complex linear assets. These opportunities will be discussed in the following sub-sections.

6.2.1 Definition of failure

A fundamental question addressed in this study is the definition of “failure”. Interviews with sewer system managers did not produce a consensus definition. The definition used in this research is convenient from a systems engineering viewpoint since it relates to the design requirements of wastewater collection systems. However, it is recognized that pipes often lose conveyance capacity without any consequences of the “failure”. The significance of this distinction is that some stakeholders may find limited value in a process that identifies surcharged pipes if they are concerned only with the risk of visible overflows, public complaints, or regulatory enforcement actions. As a result, there are future research opportunities in this area that can be directed towards understanding the full spectrum of the definition of failure and adapting risk management activities to accommodate the different definitions of failure.

6.2.2 Computation of severity scores

This research proposed a convenient method for quantifying the consequences of failure on a 1-10 scale using aerial imagery. Future research may consider the varying consequences of failures based upon their magnitude. A surcharge leading to overflows of a few gallons has significantly less consequence than an overflow in the same location of thousands of gallons. Thus, future research that considers pipe sizes and flow rates in the severity score rubric would help develop further understanding of the potential worst-case scenarios. This research could be furthered by incorporating hydraulic models that estimate affected land and water bodies under a range of overflow scenarios. Future research that presents the consequences of failure in the form of a distribution of potential impacts at each location or class of locations would be beneficial to decision makers. Considering the migration of contaminated water once it reaches the surface would lead to a better understanding of consequences, particularly when the consequences are far away from the point of failure.

6.2.3 Computation of occurrence scores

Occurrence scores in this research were based on 30 days of level monitoring data. This was somewhat arbitrary and motivated by selecting a duration that would be considered short, and thus affordable. Future research might explore the question of an optimal monitoring period that balances cost with prediction accuracy. Future studies can utilize velocity sensors, available in modern flow monitors, to improve forecast accuracy through analysis techniques such as scatterplots of depth and velocity relationships (Enfinger and Stevens 2006). Future research might also explore estimating failure probabilities in non-circular pipes. Other shapes should be examined with the expectations that the general methodology will apply but the equations for calculating occurrence ratings will be different.

6.2.4 Alternative search objectives

The objective function selected for this research prioritizes low cost over finding the absolute highest risks by setting classifying risk levels as either acceptable or not acceptable. This choice accepts that locations of global highest risk will not be actively managed because lower risks, which were discovered sooner, will receive attention. Presumably, systems operators could prioritize management actions in order of RPN within the unacceptable risk category. In the course of the research, search duration became a consideration. Future research that formulates the problem as a multi-objective optimization problem could be of value in aligning the competing objectives to match the risk preference of the decision makers.

Three aims in this research are location of a minimum number of unacceptable risks, minimization of cost, and minimizing the trade-off of cost and search duration. Minimizing variability was considered in this research but not included as a goal for the solutions. However, the simulation constructed for this research could provide a useful platform for evaluating these approaches since the elements of time, risk, duration, and some inherent variability are available in the simulation output.

An intriguing possibility for a next step is to augment the process proposed in this research with a very limited number of a different type of agent who perpetually search for locations of higher risk, guided by the ESA algorithm. The use of a single agent was shown to be very efficient in discovering risky locations. This approach could justify the extra expense of a set of continuously searching agents by finding locations of higher risk than those that meet the criteria of unacceptable risk.

6.2.5 Added realism to simulations

The baseline simulation in this research assumes a theoretical distribution of risk occurrence ratings, calibrated to overflow data. Prior research into mathematical models for forecasting blockages casts doubt on theoretical distributions based on inferential statistics as it supports the variation of explanatory variables from system to system. More data, in addition to overflow data, would lead to a better understanding of incidents of pipe surcharge. This research attempted to mitigate the effect of these assumptions through calibration to available data and by a sensitivity analysis involving a range of possible risk distributions. Additional effort can confirm how well the various conditions represented the state of actual sewer systems. Future research that examines the impact of these conditions and/or accommodates the variation of explanatory variables might improve the accuracy of the model predictions and the validity of the simulation model vis-à-vis the real world.

6.2.6 Data from continuous monitoring

An important benefit of continuous monitoring with movement iterations is that it will make available much more data on the state of collection systems than is currently available. The advent of the internet-of-things (IoT) is making analytical tools increasingly available. The scarcity of data on the hydraulic performance of drainage systems inhibits the application of these tools to managing one of the most critical infrastructure systems in developed countries. Yet, analysis of big datasets should provide a much better understanding of the mean time between potential failure and functional failure for common failure modes of sewers, in addition to the possibility of forecasting the progression of potential failures for the purpose of determining optimal intervention times. Furthermore, it might also inform the decision of when to install continuous monitors. Potential failures that develop very slowly might be ignored in the early period of formation, deferring monitoring until potential failure is more imment.

Therefore, further research into the development of mathematical prediction models for failure, aided by continuous monitoring data, would be beneficial. Prior research indicates that predictor variables and coefficients vary for each specific sewer system and that it is a slow and difficult process to develop the models due to the condition of the available data. To overcome this problem, continuous monitoring data can be geocoded and cross-referenced to GIS systems which will facilitate future model development, including the ability to customize each model to the system where it will be used. Further research can foster greater understanding of the information contained in depth-to-diameter ogives. The data relations revealed in the ogives have not been commonly used in collection system performance analysis. Thus, research using modern machine learning classification algorithms would be an interesting research area. A tentative hypothesis of this research is that the shapes of the ogives would reveal some of the more common failure modes in sewers, such as the accumulation of grease, sediment accumulation, root intrusion, and excessive rain water infiltration and inflow, through the use of a single measurement entity – water level. Understanding the failure mode would suggest times for optimal intervention and the type of intervention needed.

6.2.7 Enabling technologies to discover potential failures

This research aids the potential for discovery of a subset of failures that utilities can afford to actively manage. This research can provide a means for utilities to guide the allocation of limited budgets to efficiently find valuable locations for risk management. New technologies are needed to enable these limited budgets to afford full-scale system monitoring. These technologies will be less expensive and/or capable of sensing across very large areas.

6.2.8 Future research area summary

It would be beneficial for future research to define the optimal monitoring period for making estimates of failure probability. Longer periods might lead to better accuracy than the 80% achieved in this study, while shorter periods may maintain the same level of accuracy at lower cost. There is value in additional research in understanding the probability distributions of risky locations. The available information for this study were theoretical distributions of surcharge and observed overflow information. There was no data available regarding empirical pipe surcharge probability distributions. This prompted this research study to look at the robustness of the risk assessment techniques to a wide range of distributions. An understanding of the range of failure distributions across many collection systems would allow further optimization of the search parameters. In addition, more research is needed into the technologies that would enable wide-scale deployment of continuous monitors. This would make it possible to know the state of an entire collection system all the time to potentially achieve the ultimate goal of eliminating all impacts from sewer failures.

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APPENDIX A

This appendix contains unedited data collected by ADS Environmental Services in the course of flow monitoring projects conducted in seven cities in the United States during the period from 1 September 2017 to 1 October 2017. The projects were selected randomly from a larger database of projects with a total of 447 monitoring locations included in the sample. From this sample, a total of 141 of the locations in six cities recorded surcharge (zero free capacity) during the sampling period.

A lookup table constructed using a hydraulics elements curve was used to calculate pipe carrying capacity at each decile of d/D as a percentage of full pipe capacity (O'Shea 2019). The relationship is presented graphically in figure (A-1).

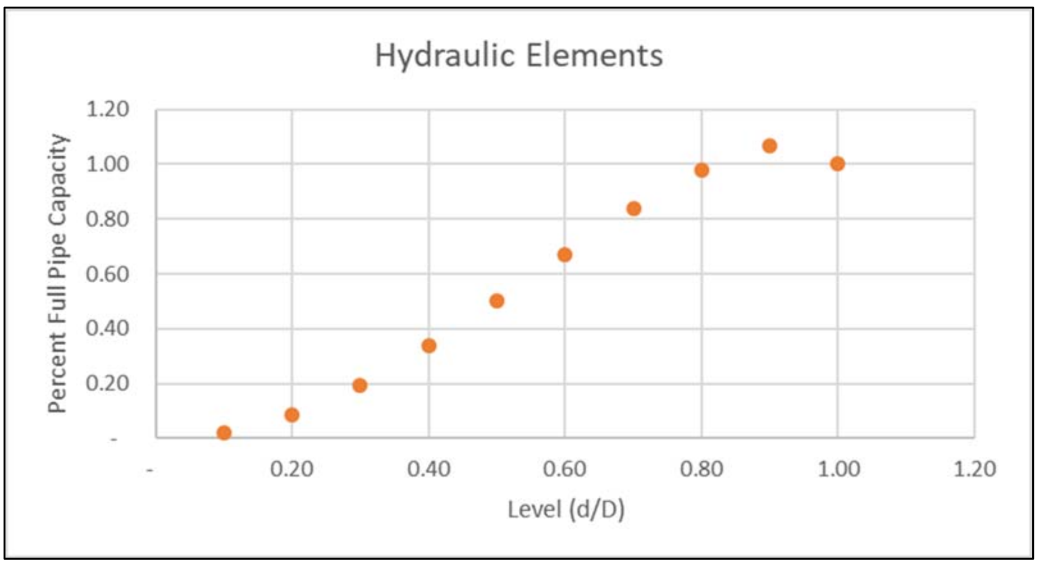

Figure A-1: Pipe carrying capacity at each d/D level

For each location, a bias correction was added so that no pipe was allowed to carry more than its design capacity at any water level and the average flow rate recorded by the flow monitor was divided by the full pipe flow rate recorded by the flow monitor for each d/D decile. This data is shown in table (A-1) with each row in the table representing a monitor location. It is worth noting that eighteen locations were removed from the sample because the results were negative. A location was labelled “Fully Functional” if it achieved 100% of design capacity at full pipe. The results show that the pipes that recorded surcharge did so at a mean of 76% of their design capacity. The results also show that 16% of the sample conveyed their design capacity.

Table A-1: Percentage of design capacity at each monitor location

Project ID	Pct. Design Capacity	Fully Functional?
1	81%	0
1	95%	0
1	100%	1
1	90%	0
1	94%	0
1	79%	0
1	85%	0
1	100%	1
1	98%	0
1	77%	0
1	85%	0
1	82%	0
1	70%	0
1	15%	0
1	83%	0
1	86%	0
1	77%	0
1	64%	0
1	40%	0
1	50%	0
1	97%	0
1	56%	0
1	72%	0
1	49%	0
1	51%	0
1	83%	0
1	52%	0
1	85%	0
1	51%	0
1	70%	0

Project ID	Pct. Design Capacity	Fully Functional?
1	98%	0
1	85%	0
1	24%	0
1	88%	0
1	91%	0
1	96%	0
1	84%	0
1	96%	0
1	90%	0
1	92%	0
1	95%	0
1	100%	1
1	92%	0
1	55%	0
1	54%	0
1	87%	0
1	100%	1
2	64%	0
3	55%	0
3	100%	1
3	100%	1
3	91%	0
3	100%	1
3	25%	0
3	100%	1
3	15%	0
4	17%	0
4	76%	0
4	51%	0
4	85%	0
4	92%	0
4	78%	0
4	98%	0
4	62%	0
4	93%	0
4	100%	1
4	94%	0
4	93%	0
4	56%	0
4	72%	0
4	51%	0

Project ID	Pct. Design Capacity	Fully Functional?
4	46%	0
4	73%	0
4	87%	0
4	67%	0
4	100%	1
4	47%	0
4	78%	0
4	97%	0
4	100%	1
4	100%	1
4	92%	0
4	55%	0
4	59%	0
4	100%	1
4	100%	1
4	63%	0
4	51%	0
4	100%	1
4	59%	0
4	53%	0
4	100%	1
4	40%	0
4	42%	0
4	93%	0
4	100%	1
4	42%	0
4	66%	0
4	95%	0
4	90%	0
4	61%	0
4	29%	0
5	100%	1
5	78%	0
5	98%	0
5	93%	0
5	92%	0
5	83%	0
5	86%	0
5	52%	0
5	100%	1
5	95%	0

Project ID	Pct. Design Capacity	Fully Functional?
5	81%	0
5	79%	0
5	15%	0
5	28%	0
5	93%	0
5	90%	0
5	71%	0
6	100%	1
6	78%	0
6	76%	0
Mean	76%	
Proportion Fully Functional		16%