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Multi-segment multi-criteria approach for selection of trenchless construction methods

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MULTI-SEGMENT MULTI-CRITERIA APPROACH FOR SELECTION OF TRENCHLESS CONSTRUCTION METHODS

by

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ABSTRACT

The research work presented in this thesis has two broad objectives as well as five individual goals. The first objective is to search and determine the minimum cost and corresponding goodness-of-fit by using a different combination of methods that are capable of resolving the problem that exists in multiple segments. This approach can account for variations in unit price and the cost of the design and the inspection associated with multiple methods. The second objective is to calculate the minimum risk for the preferred solution set. The five individual goals are 1) reduction in total cost, 2) application of Genetic Algorithm (GA) for construction method selection with focus on trenchless technology, 3) application of Fuzzy Inference System for likelihood of risk, 4) risk assessment in HDD projects, and 5) Carbon footprint calculation.

In most construction projects, multiple segments are involved in a single project. However, there is no single model developed yet to aid the selection of appropriate method(s) based on the consideration of multiple-criteria. In this study, a multi-segment conceptualizes a combination of individuals or groups of mainlines, manholes, and laterals. Multi-criteria takes into account the technical viability, direct cost, social cost, carbon footprint, and risks in the pipelines. Three different segments analyzed are 1) an 8 inch diameter, 280 foot long gravity sewer pipe, 2) a 21 inch diameter, 248 foot long gravity sewer pipe, and 3) a 12 inch diameter, 264 foot long gravity sewer pipe. It is found that GA would not only eliminate the shortcomings of competing mathematical

approaches, but also enables complex optimization scenarios to be examined quickly to the optimization of multi-criteria for multi-segments.

Furthermore, GA follows a uniform iterative procedure that is easy to code and decode for running the algorithm.

Any trenchless installation project is associated with some level of risk. Due to the underground installation of trenchless technologies, the buried risk could be catastrophic if not assessed promptly. Therefore, risk management plays a key role in the construction of utilities. Conventional risk assessment approach quantifies risk as a product of likelihood and severity of risk, and does not consider the interrelation among different risk input variables. However, in real life installation projects, the input factors are interconnected, somewhat overlapped, and exist with fuzziness or vagueness.

Fuzzy logic system surpasses this shortcoming and delivers the output through a process of fuzzification, fuzzy inference, fuzzy rules, and defuzzification. It is found in the study that Mamdani FIS has the potential to address the fuzziness, interconnection, and overlapping of different input variables and compute an overall risk output for a given scenario which is beyond the scope of conventional risk assessment.

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Date 08-05-13

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CHAPTER 1

INTRODUCTION

1.1 Introduction and Background

Several models and algorithms are described in the literatures which are geared towards a suitable method or technique for the rehabilitation of water and wastewater networks. Over the past 40 years, the trenchless technology industy developed a set of methods, materials, and equipment for the rehabilitation and new installation of underground infrastructures that inflict minimum disturbance on paved areas and business activities (Allouche, 2001). However, a key concern is that the chosen method or technique provides an optimum solution to the project at hand. Therefore, selection criterion for an optimum construction method ideally ensures a satisfactory technical solution, while simultaneously consider other parameters such as cost, carbon footprint, and risk, as to optimize the overall outcome of the project.

In most real-world cases, multiple segments with varying attributes are involved in a single project. Therefore, an optimization of the solution must be made for those multiple pipe segments. Although the use of different methods for different segments might be justifiable from a sole technical prospective, it may not be feasible when a wider consideration of costs, carbon footprint, and risk takes place. This is common problem in multi-segment.

Hence, one way to determine the optimal solution for multiple line segments is to minimize the number of methods and their anticipated total costs, which include direct cost and social cost (Matthews, 2010).

In addition to direct cost and social cost, carbon offset or carbon cost is a quantifiable parameter that can be included in the analysis. Carbon offset not only has an impact on the environment, but also lends itself to the calculation of the cost per ton of carbon emissions. Since the environment and sustainability are key concerns for many of the stakeholders associated with construction and rehabilitation, the interest in carbon offset is neither negligible nor insignificant. Therefore, an optimal solution to multi-segments should be aimed at minimizing direct costs as well as social, and carbon costs.

Any trenchless installation project is associated with some level of risk. However, risk is not addressed properly in many projects, which results in poor project performance (Tah & Carr, 2000). Due to limited access inherent in trenchless methods, the consequence of a failure could be catastrophic. Therefore, risk management plays a key role in the construction of buried utilities. A new approach utilizing fuzzy logic was developed to better quantify risks and account for the dependency that exists among various risk factors.

1.2 Objective

The interest in genetic algorithm (GA) is accelerating as it is emerging as a robust approach towards search and selection. For the repair and rehabilitation of sewer networks, and consequently the selection of optimum methods for the multi-criteria analyses, GAs provide useful and valuable results (Halfawy et al., 2009). According to

Malkawi et al. (2004), genetic algorithm is a form of artificial intelligence that aids optimization in decision making and improves the solution of the optimization problem. For optimization of design decisions, it adapts a generate-and-test approach.

Tools and websites (Islam et al., 2012) have been developed to enhance computer-augmented decision support system for trenchless technologies, covering both installation and rehabilitation. Yet, none of these are individually sufficiently capable of providing a comprehensive solution to the challenges coupled with trenchless installation risk quantification. In this regard, a fuzzy logic system was studied extensively and its potential for the quantification of risks associated with the installation and rehabilitation of trenchless technologies was evaluated.

Thus, the optimum method set would generate a solution that has minimum direct and equivalent costs and minimum risk in multi-segment trenchless projects. The solution set for a multi-segment can be a single method or multiple methods. However, the objectives are a) to search and determine the minimum cost and corresponding goodness-of-fit by using a different combination of trenchless construction methods that are capable of resolving the technical limitation and constraints that exists in multiple pipe segments, and b) to calculate the minimum risks for the preferred solution set. Therefore, this research work has the following goals:

1. Reduction in total cost (direct and indirect)
2. Application of GA for method selection
3. Application of Fuzzy Inference System for estimating the likelihood of risk for a given project
4. Carbon footprint calculation

1.3 Methodology

The methodology adopted in this study is a combination of qualitative and quantitative research. The qualitative information is based on available data reported for various projects and technologies. The data primarily consists of a review of the technical literature and the TTC (www.ttc.latech.edu) in-house databases. When sufficient data was gathered about the project requirement, analysis commence by applying genetic algorithm, followed by fuzzy logic. This analysis provides quantitative information about the project's overall cost, carbon footprint, risk, and a selection of appropriate methods for the rehabilitation or repair of the various segments. Therefore, this methodology offers a balance between qualitative and quantitative research (Creswell, 2003).

Besides data collection and analytical setup, search for appropriate and up-to-date literature provides the current state-of-the-art in this research arena. Although literature study is conceptualized as a secondary data source, these are requisite for the better understanding and solution of the research problem (Ghauri & Grønhaug, 2005).

1.4 Thesis Organization

The main components of the work in this dissertation are organized as follows: The research work presented in this thesis is divided into seven chapters (Figure 1.1), namely: 1) Introduction, 2) Literature Review, 3) Multi-segment Multi-criteria optimization, 4) Social Cost and Carbon Cost, 5) Fuzzy Logic Theory and Analysis of Likelihood, 6) Risk Assessment of HDD projects, and 7) Conclusions and Recommendations.

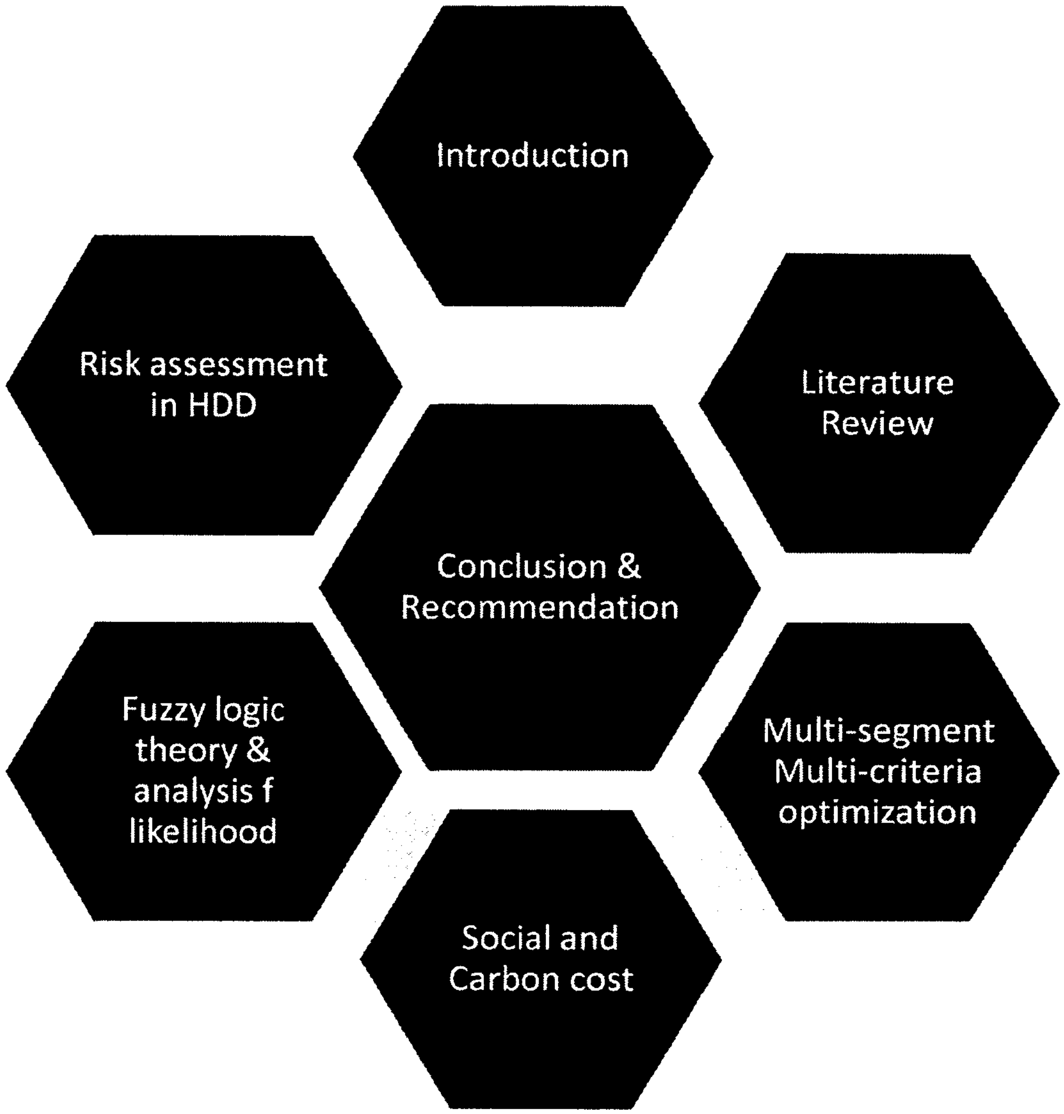


Figure 1.1: Thesis organization

CHAPTER 2

LITERATURE REVIEW

2.1 Background of Multi-Segment Optimization

2.1.1 Multi-Segment Optimization

A segment is a combination of individuals or groups of mainlines, manholes, and laterals. Based on the names and numbers, the segments are divided into three categories: a) a segment that has a mainline, a manhole, or a lateral separately; b) a segment that has a mainline and a manhole; and, c) a segment that has a mainline, a manhole, and a lateral (Figure 2.1). A multi-segment generally consists of a number of segments.

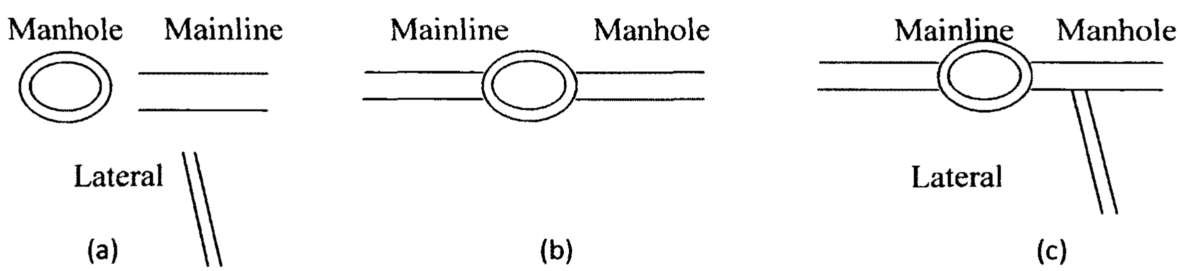


Figure 2.1: Different pipeline segments

According to Goldberg (1989), optimization is the process of seeking the best. The approach for the best performance or solution towards an optimal point is a two-lane road. First, optimizations strive to improve the process; second, optimizations drive the solution to reach the optimal point. Traditionally, optimization means convergence that leads to an optimum method. However, it fails to interpret the interim performance and related improvements properly. Therefore, in many cases, a global optimization becomes hard to obtain. The phenomena of the natural selection process can be mimicked here, as its goal is to select an optimum method by seeking continuous improvements as well as goodness-of-fit.

The prime objective of multi-segment optimization is to select the best optimal method(s) for rehabilitation/repair of the segments. In this regard, the optimization process of the multi-segment pipe(s) can be explained by using it to evaluate a real-world example that involves multiple line segments needing to be replaced or rehabilitated. The three line segments from an actual construction project undertaken by the city of Edmonton, Alberta, as part of the Southside Sewer Relief program in the 1990s (Parhami 2004) are used to demonstrate how the proposed algorithm can be used in practice. All three segments were analyzed with TAG and TAG-R to determine which methods were technically viable (Matthews, 2010). Details are described in the case history section.

2.1.2 Multi-Criteria Optimization

Multi-criteria optimization can be conceptualized from the difference between multi-criteria and single criteria optimization. Multi-criteria searches for the best compromise between several objectives in the search space (Cho & Hastak, 2013; Abraham & Jain, 2005; Jaszkiewicz, 2002; Coverstone-Carroll et al., 2000); the single criteria searches for a single optimal solution such as cost, quality, or time (Abraham & Jain, 2005; Coverstone-Carroll et al., 2000). The advantage of multi-criteria optimization is that it can define complex problems better by defining every criterion. However, there are not enough well-developed techniques to describe multiple optimizations (Abraham & Jain, 2005). Moreover, the problem solving process in the case of multi-criteria is cumbersome and time consuming, in comparison to single criteria optimization.

Although multi-criteria optimization has some shortcomings, it is still a preferable choice due to the simultaneous optimization of multiple objectives. For example, the completion of a successful project is grounded in the optimization of cost, quality, and time. The optimization of these three parameters is possible by using the multi-criteria analysis. However, it may not be possible to optimize these three parameters by single criteria analysis. Although the cost and time parameter could be quantified in monetary terms, there is hardly any unique way to calculate all aspects of quality parameters.

However, it is not always necessary in multi-criteria analysis that the best solution set represent the best of every criterion, but that it generates the most efficient solution sets (Jaszkiewicz, 2002). Therefore, the the optimum solution could be a trade-off among different criteria (Cho & Hastak, 2013) and the best solution can be a combination of the best for one criterion, the second best for another, and so on. According to Abraham and Jain (2005), the optimal result is likely to be obtained if other solutions of the search space do not dominate it. This type of non-dominated solution is termed as Pareto-optimal. In a multi-criteria analysis, the Pareto-optimal set supports the real-world decision making process by generating the best possible outcome.

2.2. Genetic Algorithm

Sheble and Maifeld (1994) defined genetic algorithms (GA) as global optimization techniques depending on genetics and natural selection phenomena. The process of evolution, natural selection, and route of operations was of great interest among the researchers in solving complex problems. Coding of genetic algorithms was done in the form of string structures followed by binary digits. Although GA is a form of evolutionary algorithm (Ashuri & Tavakolan, 2012), the searching mechanism is based on the survival-of-the-fittest or goodness-of-fit theory. According to the problem statement, a set of string structures are created, then the fittest structures are selected for further consideration. The chance of further selection increases exponentially according to the fitness of the structures (Figure 2.2). This procedure continues until convergence occur (Kandil & El-Rayes, 2006) and the selection is narrowed down to the area of the best performance.

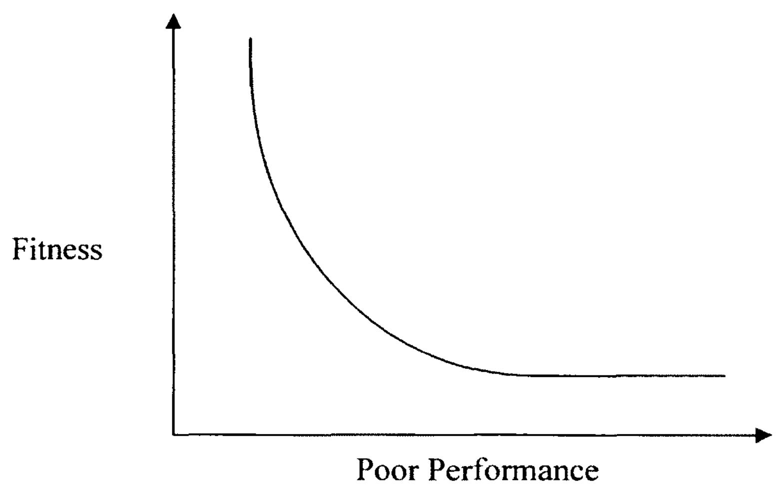


Figure 2.2: Fitness versus poor performance graph

There are three basic operators (Figure 2.3) in GA namely reproduction (or selection), crossover, and mutation (Kandil & El-Rayes, 2006; Geem et al., 2001; Sheble & Maifeld, 1994; and Holland, 1992).

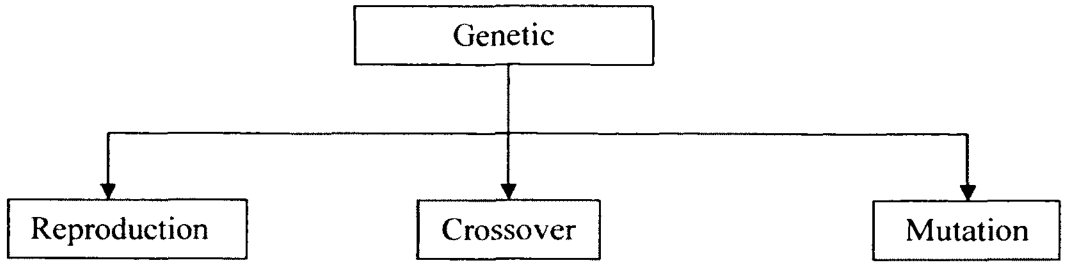


Figure 2.3: Three basic operators in GA

Reproduction: Reproduction determines the most appropriate string among the existing string sets. Typically, the next generation strings are produced by the reproduction of present strings. However, this selection process is not a random phenomenon. It undertakes the exponentially increasing trials in generating new strings based on the demonstrative performance. Likewise, pertinent information regarding the string fitness is delegated to the next generation.

Crossover: Crossover allows the strings to interact and swap information between two parent strings to produce offsprings. In the aftermath of mixing and recombination of the strings, the newly created offspring are more competent to explore new areas in the search space.

Mutation: Mutation is the process of creating non-recursive offspring and often perceived as a secondary operator. However, the continuous improvement and update of the strings are possible due to their mutation. Mutation sets the strings forward to change their value with time, thereby, the strings' positions and values cannot remain fixed.

The searching and selection model in a genetic algorithm can be described by the example of building blocks (Sheble & Maifeld, 1994). In this example, the highly fit low-order schemata are regarded as the building blocks which remain at the ground level and construct a strong foundation. The blocks exchange information through a crossover and pass it to the next upper level. Thus, the fittest strings reproduce, crossover, and move to the next level. In this way, the best and fittest string survives and reaches the top.

2.3 Fuzzy Inference System

2.3.1 Sugeno-Type Fuzzy Inference System

The Sugeno fuzzy inference system approach is systematic, computationally efficient, and has long been used in control problems and dynamic systems (Kaur & Kaur, 2012). Although the Sugeno model is data driven, it follows the basic flow chart of a fuzzy logic system comprising of fuzzy rules and membership functions for an input-output variable (Behret et al., 2011). However, the ultimate defuzzification process is different for Sugeno and Mamdani fuzzy models (Kaur & Kaur, 2012). The Sugeno model typically uses the weighted average method to generate crisp output, whereas the Mamdani model utilizes the expert knowledge to produce the final output. The most common form of Sugeno model rules are IF and THEN. For example,

$$IF\ input\ x = a\ and\ input\ y = b$$

$$THEN\ output\ z = ax + bx + c\ \ (where\ c\ is\ a\ constant)$$

The value of z becomes constant when it is a zero-order Sugeno fuzzy model. In this case, the value of a and b equals to zero ($a=b=0$). The model also has the flexibility to turn into a first-order polynomial (or a first-order Sugeno fuzzy model). Typical, first-order Sugeno model delivers fuzzy crisp outputs through weighted average or weighted sum method. Significant complexity could arise in the case of higher order Sugeno fuzzy models. Furthermore, the compositional rule for membership functions and their fuzzy inference are not smooth in this model. In contrast, Mamdani fuzzy model is based on expert knowledge. It is intuitively overlapped, manually constructed, and flexible to obtain a generalized model for decision support system (Kaur & Kaur, 2012; Behret et al., 2011).

2.3.2 Mamdani-Type Fuzzy Inference System

Mamdani fuzzy logic, an offspring of fuzzy logic system, can be used for multi-input single-output (MISO) risk quantification (Kumar et al., 2012). This makes it a suitable candidate for MISO risk analysis for trenchless installation projects, since typical installation projects have a set of multiple risk inputs and requires to find an overall risk score. Therefore, utilization of Mamdani fuzzy logic could be considered a promising approach for the risk quantification of projects of a similar nature.

The fuzzy inference system (FIS) is governed by rules which forms the control strategy, and are based on expert knowledge (Abdullah & Rahman, 2012; Kaur & Kaur, 2012; and Behret et al., 2011). Furthermore, this rule base has the advantage to sync with linguistic rules that makes it ideal for the decision support system. Due to the application of expert knowledge, Mamdani FIS reduces the computational burden (Kaur & Kaur 2012) and is capable of generating a pliable model (Behret et al., 2011) to address future uncertainties such as risk.

CHAPTER 3

MULTI-SEGMENT METHOD SELECTION OPTIMIZATION

3.1 Introduction and Background

Based on applications to specific fields, method selection models can be classified into three categories: general models, wastewater models, and water models (Matthews et al., 2011). General models combine both, wastewater and potable water networks. The two general models found so far in the form of software are TAG-R (Trenchless Assessment Guide for Rehabilitation) and REST (Renewal Engineering Selection Tool) (Maniar, 2010). TAG-R directly collects input from the data available in the planning phase and outputs the technically viable alternatives; REST outputs the technically viable alternatives along with a ranking factor for each. Another model developed in Europe for the decision support of wastewater is CARE-S (Computer Aided Rehabilitation of Sewer Networks for Sewers) (Saegrov & Schilling, 2004). As far as the decision support system (DSS) related to water networks, proposed models include CDSS (Comprehensive Decision Support System) by Deb et al. (2002), and the model developed by Ammar et al. (2010). The particular focus of this paper is the method selection models and algorithms for wastewater collection networks.

Various method evaluation models with high, low, and medium flexibilities were developed by researchers on the basis that an algorithm can handle multiple methods. For example, the DS'2 model (Decision Support System for Drilled Shafts) guides the decision makers in the design and construction of drilled shafts by using an expert algorithm that demonstrates medium flexibility with tangible and intangible attributes (Allouche, 2001). Moreover, a multimedia decision support system was developed to select the rehabilitation, construction, and maintenance techniques for buried pipes (Matthews, 2010). However, none of these methods address direct costs, social costs, and carbon costs for multi-criteria, multi-segment projects. This resonate with the findings by Matthews et al. (2011) that there is no stand alone tool currently available that is sufficient to evaluate the sewer projects on a multi-segment.

In DSS, the method selection algorithms play a key role in the selection of an optimal solution. Mainly, three types of algorithms are predominant: fuzzy set theory, expert systems, and neural networks (Allouche, 2001). Fuzzy set theory is comprised of numerical data and a set of equations, while the expert system and neural network are associated with the artificial intelligence arena. While the expert system applies computer codes to pick a simplified solution of a complicated problem by using the cumulative knowledge and experience of several experts, the neural network essentially imitates the human brain.

The expert algorithm follows the IF-ELSE loop along with a couple of thumb-rules, whereas the neural network builds a relationship between input and output by assigning a weighing factor to multiple interconnections. Hence, these approaches to the decision support systems for solving problems associated with multi-method and multi-criteria could be considered.

Two other possible approaches for multi-segment, method selection optimization are AHP (analytical hierarchy process) and GA (genetic algorithm). The objective of AHP is to integrate data and experience for robust decision making. AHP is further classified into two, three, or a higher level of hierarchy according to the single criteria, multi-criteria, and alternatives. On the other hand, GA is consistently becoming an avenue of research for the optimization of multi-segments, multi-objectives projects. It was found that GA could optimize both single criteria optimization through Goldberg algorithm (Goldberg, 1989) and multi-criteria through Pareto optimal front (Halfawy et al., 2009).

The genetic algorithm applied in a Two Method Solution set for a multi-segment analysis was originally developed by David Goldberg, and known as Goldberg's algorithm (Goldberg, 1989). This algorithm combines multiple criteria into a single criteria optimization. For example, the optimization parameter in this study is the cost associated with each technically viable method for the rehabilitation of the multiple pipe segments.

Whatever we construct affects the environment in either a positive way or negative way. The negative effects of construction, such as noise and air pollution, are borne by the community, not the contractual parties. For example, the noise pollution could concern people in surrounding properties, and could reduce productivity. Likewise, air pollution is associated with various gases and carbon dioxide emissions through machineries and equipment used in construction. Furthermore, traffic delays increase the fuel consumption and vehicle ware due to additional time of travel. These costs are generally referred to as 'Social Costs'. In this study, social and carbon costs of construction projects were calculated and incorporated into the decision making process.

3.2 Traditional Mathematics-Based Approach

The mathematical approach described in this thesis identified the optimum solution by evaluating all combinations of methods capable of installing, replacing, or rehabilitating each pipe segment (a solution set). The technically feasible methods were collected from TAG-R analysis of methods. The TAG-R analysis will provide the number of feasible methods for each segment based on its own particular input factors.

The total number of method set is the direct product of number of segments and number of methods capable of solving the problem of that segment. Equation 3.1 shows the total number of method set as a direct product of technically viable methods for each segment (such as S_1, S_2, S_3...S_m). For example, there are seven segments in a study and each segment contains seven solution methods. Then, there will be a 7x7x7x7x7x7x7 = 7^7 = 823,443 number of methods combination. Finding the optimum method combinations out of these 823,443 requires time, resource, and effort.

$$SS_T = S_1 \times S_2 \times S_3 \ldots \times S_m \ldots\ldots\ldots\ldots\ldots\ldots (3.1)$$

In this study, a total of three segments were considered. It was found in the TAG-R analysis that there were 6 technically viable methods for segment 1, 8 technically viable methods for segment 2, and 3 technically viable methods for segment 3. Therefore, based on Equation 3.1, there will be a 6x8x3 = 144 number of method sets capable of solving the problem of these three segments. A total of 144 methods combination need to be evaluated to generate the optimum solution sets.

Though the mathematical approach is intuitive, it has its own drawback for the multi-segment analysis. Complexity of the calculation increases dramatically with an increase in the number of segments and number of methods. This is highly cumbersome to compute manually; therefore, even if theoretically possible, it is not feasible in practice because of the required level of effort.

3.3 Algorithm-Based Approach

The optimization relies on multiple iterations of searching to find the best possible solution. The system works inside a framework that includes a set of goals and objectives to optimize during the decision making process.

There are four core features in genetic algorithm (Goldberg, 1989):

1) GA utilizes information as an objective function, not like derivatives or auxiliary information. In an objective function, the best information is chosen by evaluating the existing parameters related to string structure.
2) GA determines the best possible outcome through a guided search based on the coding of parameters, not the parameters themselves.
3) The GA searching process consists of multiple points, not only by a single point. Moreover, the multiple points in a solution space can be considered at one time.
4) GA does not apply the deterministic formulas; it uses probabilistic rules for moving from one set of solutions to another.

GA is regarded as an offspring of EA (Evolutionary Algorithm); they both have similar characteristics such as population-based evolution, fitness evaluation, multiple point exploration, non-dependence on gradient information, and stochastic search (Ding et al., 2011; Shelbe & Maifeld, 1994; Goldberg, 1989). The computational process of GA is iterative, and follows some main steps from conception to completion of the task (Ding et al., 2011; Ani et al., 2010; Verma et al., 2010; Shelbe & Maifeld, 1994). These steps are string representation, initialization, fitness calculation, selection, crossover, mutation, evaluation, generation, and solution. A basic flow chart of GA is shown in (Figure 3.1) based on these steps.

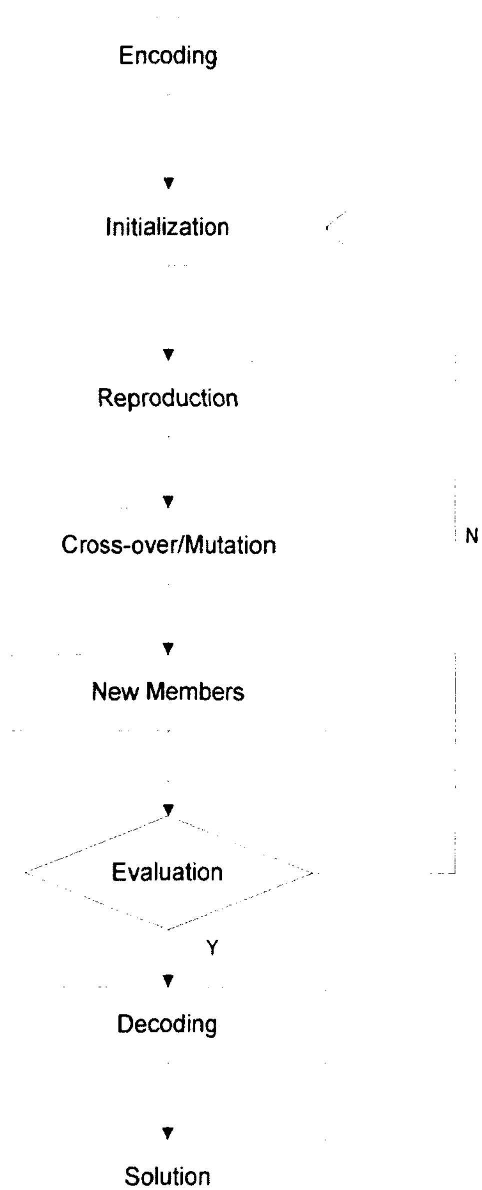


Figure 3.1: Basic flow-chart of GA

The advantage of GA is that it can run by parallel processing. If the string's structure breaks down to individual strings, the task can be done individually and parallel at the same time. In this way, multiple processors are applied to conduct concurrent searches, thus reducing run-time (the addition of processors reduces the time linearly).

Other advantages of GA include stochastic global search, wide spread applications, and reliability (Ding et al., 2011). The stochastic global searching criteria ensure global optimization and enable us to optimize the solution to a broader context. The wide spread application is observed in solving non-linear and complex problems, and evaluating the fitness of every individual. The reliability of GA is an outcome of its robustness, simplicity, and general purpose operation.

3.4 Case Histories

3.4.1 Segment 1

The first segment analyzed is an 8 inch diameter, 280 foot long gravity sewer. Besides being structurally deficient due to longitudinal cracks, it was also determined that the line needed to have an increased hydraulic capacity due to population growth in that part of Edmonton. Thus, it was decided that the sewer line needed to be upgraded to a 12 inch pipe, either by inline replacement, complete replacement, or via the installation of a parallel line segment. The need for increased capacity eliminated rehabilitation options, leaving only new installation and inline replacement methods as viable options.

Segment 1 was analyzed using TAG-R software and the results are summarized in Table 3.1 (Matthews, 2010). Six methods were found to be technically viable, three new trenchless installation methods, open-cut excavation, and two inline replacement methods.

Table 3.1: Technically viable methods for Segments 1, 2, & 3

	Segment 1	Segment 2	Segment 3
Method Name	1. Pipe-Bursting 2. Micro tunneling 3. Pipe-Eating 4. HDD Midi 5. Open cut 6. Pilot-Tubing	1. CIPP 2. Micro tunneling 3. Folded Pipe 4. Pipe-Splitting 5. Spiral Wound 6. Pipe-Eating 7. HDD Midi 8. Pilot Tubing	1. Micro tunneling 2. Open cut 3. Pilot-Tubing

3.4.2 Segment 2

The next segment to be analyzed was a 21 inch diameter, 248 foot long gravity sewer. This segment had been upgraded from a 12 inch line to the new diameter due to the need for additional capacity, but the new pipe had become structurally deficient. All options were considered including new installation, inline replacement, and rehabilitation methods.

TAG and TAG-R were used to analyze the segment using the above mentioned parameters, and eight construction methods were found to be technically viable. There were three new trenchless installation methods, and two inline replacement methods capable of performing the work based on the TAG evaluation. There were also three rehabilitation methods capable of rehabilitating the sewer pipe from the TAG-R analysis (Table 3.1). Among these, CIPP was considered to be the most acceptable method for rehabilitating the segment.

3.4.3 Segment 3

The third segment analyzed was a 12 inch diameter, 264 foot long, gravity sewer, VCP pipe. The CCTV inspection revealed misaligned joints, multiple cracks, and several protrusions along the length of the host-pipe. This segment was considered to be fully deteriorated, requiring structural rehabilitation. It was determined that a new pipe should be installed, with the old alignment being abandoned, which eliminated the inline replacement and rehabilitation methods from further consideration. The TAG-R analysis; identified three methods as being technically viable: two trenchless methods and an open cut method (Table 3.1).

3.5 Cost Calculation

The total cost presented in Table 3.2 is a combination of three categories of cost: direct, social, and carbon costs. First, the individual cost corresponding to each method found in TAG-R software was calculated for these three categories. Then, the total cost is determined by adding up each individual cost. Further details of cost categories are illustrated in the following sections.

Table 3.2: Cost summary and corresponding fitness weight

Segment No.	Method Name	Direct Cost ($)	Social Cost ($)	Carbon Cost ($)	Total Cost/Ft ($)	Number	Fitness Weight
	Pipe-Bursting	33,126	6,752	120.8	143	1	1
	Micro tunneling	182,192	13,895	60.4	701	2	3
1	Pipe-Eating	80,562	13,895	120.8	338	3	2
	HDD Midi	67,991	6,632	60.4	267	4	1
	Open cut	95,188	37,418	1209.6	478	5	2
	Pilot-Tubing	197,706	13,895	60.4	756	6	3
	CIPP	29,340	3,946	26	134	7	1
	Micro tunneling	180,663	13,575	65.2	783	8	3
	Folded Pipe	27,751	3,946	26	128	9	1
2	Pipe-Splitting	37,001	6,752	130.4	177	10	1
	Spiral Wound	28,363	3,946	26	130	11	1
	Pipe-Eating	189,084	13,575	130.4	818	12	3
	HDD Midi	65,505	6,632	65.2	291	13	1
	Pilot-Tubing	208,863	13,575	65.2	897	14	3
	Micro tunneling	169,359	13,685	61.6	694	15	3
3	Open cut	89,726	35,378	1232.8	479	16	2
	Pilot-Tubing	178,502	13,685	61.6	728	17	3

3.5.1 Direct Cost

Direct costs are associated with the purchase of materials, equipment costs, and labor. Indirect costs stem from administration, management, and overheads. The direct cost for each method was compiled from the TTC (www.ttc.latech.edu) bid price database and summarized in Table 3.2.

3.5.2 Social Cost

Social costs are generated from negative effects of construction such as noise, air pollution, and traffic delays. Moreover, social costs are borne by the community, not the contractual parties involved in the construction processes (Allouche & Gilchrist, 2004). A great deal of loss is involved in social costs as they consumes resource, diminish productivity, decrease the value of properties, and deteriorates ecosystem. Social cost for each segment were calculated using the Social Cost Calculator (ttc.latech.edu/scc/SocialCost.exe), and are presented in Table 3.2. The durations for each construction method had to be estimated to be able to determine the full social impact of each method considered to be technically viable.

3.5.3 Carbon Cost

The quantity of carbon depends on the length and diameter of the pipe, depth of the backfill, amount of daily traffic, time of operation, and fuel efficiencies (liters/day). Carbon emission is calculated for each segment using NASTT's Carbon Calculator (http://www.nastt.org/carboncalculator) and are summarized in Table 3.2. Generally, the carbon calculator provides the amount of carbon dioxide emission in tons. Per ton cost of carbon is assumed at $40 and multiplied with the amount of carbon emission to get the carbon cost. According to the 2008 market, to trade carbon offset for land use in the US, the typical range of low or high price of CO2 per ton was $2 to $50. The value of $40 was chosen to be conservative.

3.6 Multi-segment Analysis and Results

3.6.1 Mathematical Approach

3.6.1.1 Pair-Wise Comparison

The pair-wise comparison addresses two methods at a time and compares their suitability for the multi-segments. Table 3.3 demonstrates a comparison between Microtunneling and HDD Midi. It is found in Table 3.1 that microtunneling is a suitable method for segment 1, segment 2, and segment 3; and HDD Midi is a suitable method for segment 1, and segment 2. Therefore, a value of 1 and 0 is assigned based on the technical suitability/viability of the method. Its value is 1 if technically viable, and 0 is technically unsuitable. For a two method solution set, the sum of each pair of column cannot be zero.

Table 3.3: Pair-wise method comparison.

	Segments		
Methods	S_1	S_2	S_3
Micro tunneling	1	1	1
HDD Midi	1	1	0
Σ	**2**	**2**	**1**

In some cases, the two method solution set results in a null solution. A null solution is found when the sum of two columns is equal to zero. For example, a pair of method is based on Folded Pipe and Pipe-Splitting. In Table 3.4, it shows that the summation of the first and third columns of the table is zero, meaning that for this pair of solution, the result set becomes null. Therefore, a pair consists of Folded Pipe and Pipe-Splitting ultimately generates a null solution.

Table 3.4: Pair-wise method comparison – null solution.

Methods	Segments		
	S_1	S_2	S_3
Folded Pipe	0	1	0
Pipe Splitting	0	1	0
Σ	**0**	**2**	**0**

However, a pair of solution set consisting of Microtunneling and Pilot Tubing does not result in a null solution. Table 3.5 shows that the summation of the first column is 2, the second column is 1, and the third column is 2. Therefore, a pair-wise comparison for Microtunneling and Pilot Tubing results in a real solution. Not only microtunneling is capable of solving the problems of segment of 1, 2, and 3, but also Pilot Tubing is capable of solving the problems of segment 1, 2, and 3. Hence, Microtunneling and Pilot Tubing pair formulate a real solution.

Table 3.5: Pair-wise method comparison – real solution.

Methods	Segments		
	S_1	S_2	S_3
Micro tunneling	1	1	1
Pilot Tubing	1	1	1
Σ	**2**	**2**	**2**

3.6.2 Genetic Algorithm

3.6.2.1 Two Method Solution Set

The analysis consists of three segments: Segment 1 yields six methods, Segment 2 yields eight methods, and Segment 3 yields three methods. The total cost that corresponds to each method is calculated and summarized in Table 3.2. From Table 3.2, it is found that the maximum and minimum cost per linear foot of pipe is $897 and $128, respectively. Therefore, a cost range of $0 to $900 is assumed and ranked from 1 to 3 to assign the fitness weight corresponding to each method (Table 3.2). The minimum fitness value is calculated by adding all the fitness values divided by the number of initial groups formed. The fitness value for every method is either 1000 or 0, and the rule used to assign this value is provided below.

Fitness of a method = 1000; if Fitness Weight <MedLMH
Fitness of a method = 0; if Fitness Weight > or =MedLMH

The intention behind utilizing GA is to find the best method in terms of cost in a shorter time. In this regard, initial groups are created (Table 3.6) and a bar-chart is produced (Figure 3.2). In the reproduction phase, the group with relatively low fitness is excluded from further consideration (Table 3.7). It is assumed that reproduction and crossover would generate new solutions that are more fitting than the previous solution sets. If the new solution is a better fit, then it will be taken for further processing; otherwise, it will be discarded from the analysis. Finally, the best fitting solution will be determined through repeated iteration. Table 3.8 shows that there are five groups (G1, G2, G3, G5, G6) considered for one point crossover.

Table 3.6: Initial groups

Group		**NO**		**Fitness**
G1	1,10	15		2000
G2	2,8	16		1000
G3	4,13	17		2000
G4	6,14	15		0
G5	3,12	16		2000
G6	5,16	7		3000

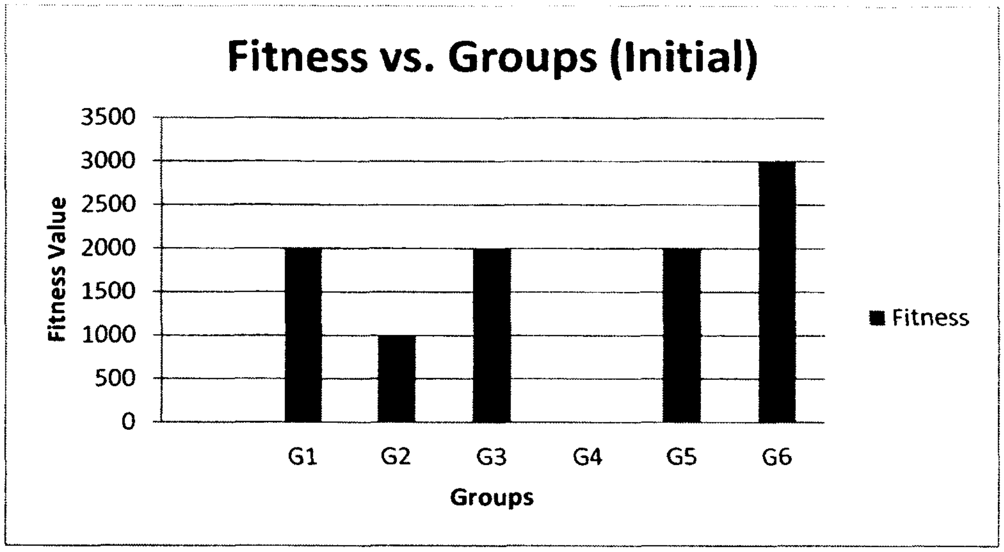


Figure 3.2: Fitness vs. groups (initial)

Table 3.7: Reproduction

Group		NO	Fitness
G1	1,10	15	2000
G2	2,8	16	1000
G3	4,13	17	2000
G5	3,12	16	2000
G6	5,16	7	3000

[Note: Group with relatively low fitness (e.g. fitness = 0) is excluded for further consideration]

Table 3.8: One point cross-over

Group	NO		Fitness
G1	1,10	15	2000
G2	[redacted]		1000
G3	4,13	17	2000
G5	[redacted]		2000
G6	5,16	7	3000

The one point crossover is conducted on the second column (Table 3.9), and genes are swapped between two groups to create new chromosome members. In the new chromosome, the members of one group are eliminated from further consideration due to their lower fitness. Therefore, only four groups (G1, G3, G4, and G6) are taken to the next cross-over (Table 3.10). Lastly, three groups are selected with the highest level of fitness (Table 3.11), while the fourth group is eliminated.

Table 3.9: New members 1

Group	NO		Fitness
G1	1,10	[redacted]	3000
G2	[redacted]	15	0
G3	4,13	[redacted]	3000
G5	[redacted]	17	1000
G6	5,16	7	3000

Table 3.10: New members 2

Group	NO		Fitness
G1	1,10	16	3000
G3	4,13	16	3000
G5	3,12	17	1000
G6	5,16	7	3000

Table 3.11: New members 3

Group	NO		Fitness
G1	1,10	16	3000
G3	4,13	16	3000
G6	5,16	7	3000

The results of the analysis are summarized in Table 3.12. There are three sets of solutions available to the problem addressed in the multi-segment. However, one of them, set 3 (open cut and CIPP) is not desirable in this case due to environmental considerations, since it will result in increased carbon emissions and social costs. Among the other two solutions, set 1 (pipe bursting and open cut) can be regarded as the most suitable for this scenario because it has the lowest total cost of $210,218 for Two Method Solution sets. The other solution, set 2 (HDD-Midi and open cut), is also feasible, but the total cost is a little higher, being about $273,221. The overall fitness of the final groups is presented in Table 3.13 with a fitness value corresponding to each group (Figure 3.3).

Table 3.12: Results

Solutions	**Segment 1**	**Segment 2**	**Segment 3**	**Total Cost ($)**	**Comments**
Set 1	Pipe Bursting	Pipe Bursting	Open Cut	210,218	Feasible
Set 2	HDD Midi	HDD Midi	Open Cut	273,221	Feasible
Set 3	Open Cut	CIPP	Open Cut	293,464	This solution is feasible but not desirable due to carbon offset and higher total cost.

Table 3.13: Final groups

Group	NO		Fitness
G1	1,10	16	3000
G2	2,8	15	0
G3	4,13	16	3000
G4	6,14	15	0
G5	3,12	17	1000
G6	5,16	7	3000

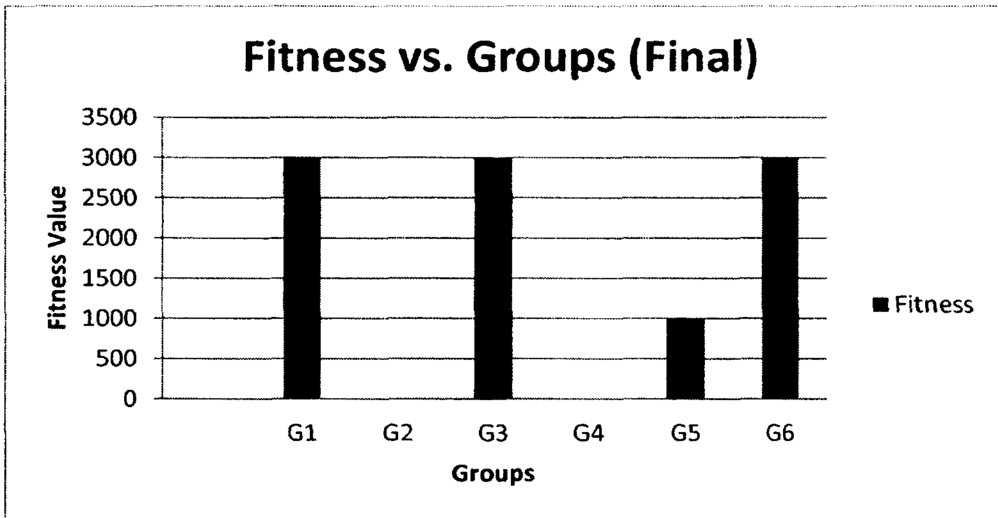


Figure 3.3: Fitness vs. groups (final)

3.6.2.2 Three Methods Solution Set

The Three Method solution in GA follows a similar procedure to the Two Method solution. However, there is a difference in the orientation of methods and the formation of initial groups as shown in Table 3.14 and Figure 3.4. Each chromosome/group contains three separate methods/genes in a group. The groups are selected by arbitrarily placing one method from one segment to a particular column. Group 6 is excluded for further consideration because of its zero overall fitness score (Table 3.15). Therefore, there are total five groups (G1, G2, G3, G5, and G4) taken for the next stage of one point crossover.

Table 3.14: Initial groups

Group		NO		Fitness
G1	1	7	15	2000
G2	2	8	16	1000
G3	3	9	17	2000
G4	4	10	16	3000
G5	5	11	14	2000
G6	6	12	15	0

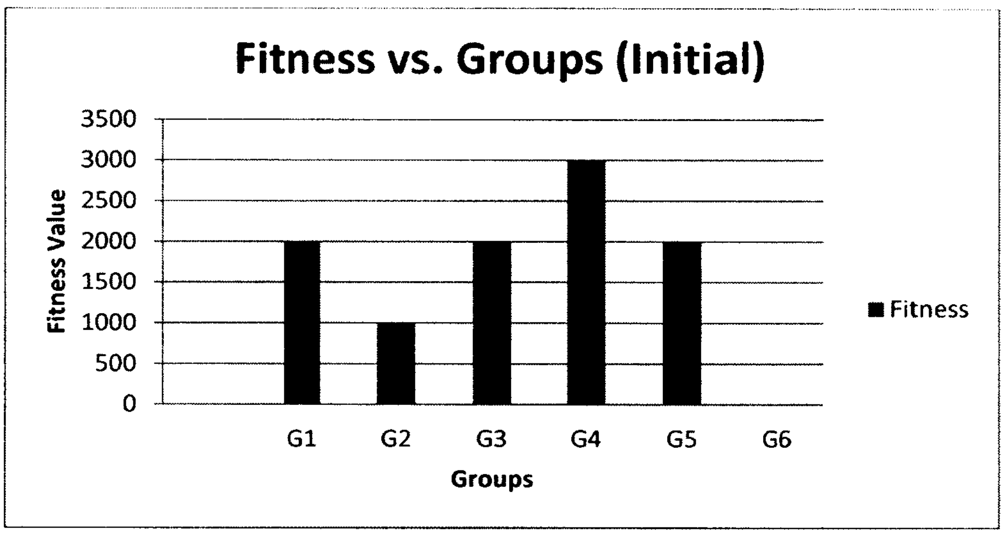


Figure 3.4: Fitness vs. groups (initial)

Table 3.15: Reproduction

Group		NO		Fitness
G1	1	7	15	2000
G2	2	8	16	1000
G3	3	9	17	2000
G5	5	11	14	2000
G4	4	10	16	3000

[Note: Group with relatively low fitness (e.g. fitness = 0) is excluded for further consideration]

The crossover point is chosen randomly in the third column of Table 3.16. The top four genes in the third column swap among themselves to create new offspring, while the bottom chromosome remains unaltered due to its best fitness value. The new members, created after crossover, are presented in Table 3.17. It is observed that the crossover increased the fitness of a new member in group 1; the member with the lowest fitness score was eliminated in Table 3.18. Finally, a new table is created by identifying the best fit chromosome of group 1 and group 4 (Table 3.19).

Table 3.16: One point cross-over

Group		NO		Fitness
G1	1	7	15	2000
G2	[redacted]			1000
G3	3	9	17	2000
G5	[redacted]			2000
G4	4	10	16	3000

Table 3.17: New members 1

Group		**NO**		**Fitness**
G1	1	7	[redacted]	3000
G2	[redacted]		15	0
G3	3	9	[redacted]	2000
G5	[redacted]		17	2000
G4	4	10	16	3000

Table 3.18: New members 2

Group		**NO**		**Fitness**
G1	[redacted]			3000
G3	3	9	14	2000
G5	5	11	17	2000
G4	4	10	16	3000

Table 3.19: New members 3

Group		NO		Fitness
G1	[redacted]			3000
G4	4	10	16	3000

The result summarized in Table 3.20 shows that there are two optimal solutions to perform this multi-segment analysis using three methods. Solution set 1 consists of pipe bursting, CIPP, and open cut yields the lowest total cost of $199,648, and it is very much a doable solution for the multi-segments built on three separate segments. Solution set 2 consists of HDD Midi, pipe splitting, and open cut yields a cost of $245,112, which is also doable. However, solution set 2 results in a higher cost than solution set 1. By switching from solution set 2 to 1, the client can save about $45,464. Therefore, solution set 1 is found more cost-effective than the other method. The final groups and fitness values are presented in Table 3.21 and Figure 3.5 respectively.

Table 3.20: Results

Solutions	Segment 1	Segment 2	Segment 3	Total Cost ($)	Comments
Set 1	Pipe Bursting	CIPP	Open Cut	199,648	Possible
Set 2	HDD Midi	Pipe Splitting	Open Cut	245,112	Higher cost

Table 3.21: Final groups

Group		NO		Fitness
G1	1	7	16	3000
G2	2	8	15	0
G3	3	9	14	2000
G4	4	10	16	3000
G5	5	11	17	2000
G6	6	12	15	0

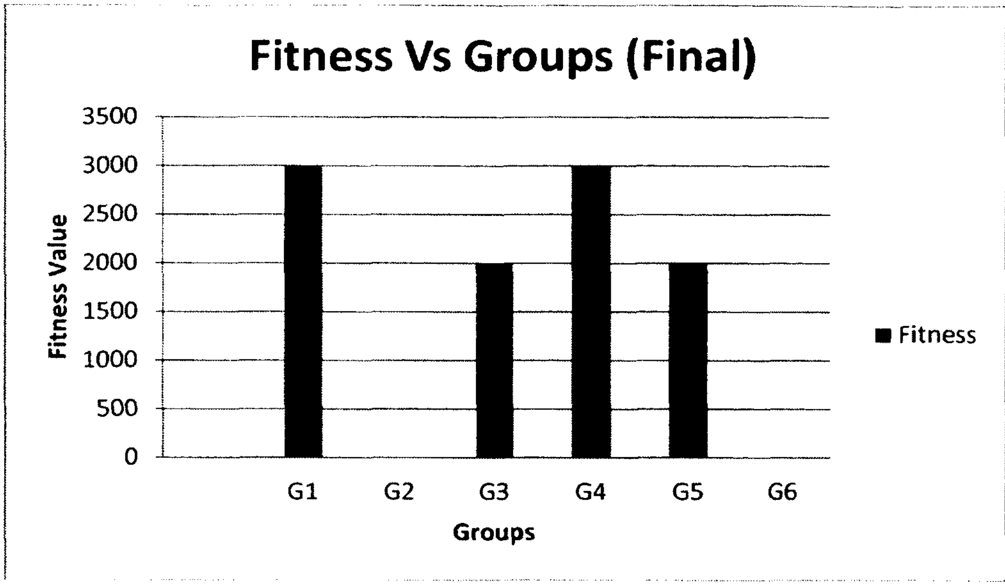


Figure 3.5: Fitness vs. groups (final)

3.7 Discussions

To assist in the optimization of multi-segment multi-criteria analysis, the genetic algorithm based approach was found to demonstrate the potential to provide solutions for multi-segment projects as well as various applications (water, wastewater). The method can also address the direct costs, social costs, and carbon costs for the multi-criteria, multi-segment projects. The application of genetic algorithm may improve this scenario by optimizing the single criteria, as well as the multicriteria of multi-segments through rehabilitation and the new installation of underground infrastructures.

Real-world, multi-segment, pipeline projects have to be optimized so that they can provide a faster, better, and cheaper solution. However, whatever we build, install, or rehabilitate must neither conflict with the environment nor affect the local community negatively. Therefore, sustainability issues should be incorporated, and social costs need to be added in the total cost of single criteria analyses for multi-segments. Although traffic delays, noises, and air pollution are included in social costs, the carbon emission (from machineries and equipments used in construction) is calculated separately.

The two models described in this paper for the optimization of total cost in three segments are the mathematical approach and the algorithm based approach. The mathematical approach is straightforward and provides logical sense to the multi-segment cost computation. For example, the Two Method (pipe bursting and open cut) solution set for the segments results in a total cost of $ 210,218 by using the mathematical approach (pair-wise comparison). It is interesting to note that GA led to the same outcome for the Two Method (pipe bursting and open cut) solution set. Furthermore, the Three Method Solution set for GA consists of pipe bursting, CIPP, and open cut with a total cost of $199,648.

While mathematical approaches apply deterministic formulas, GA inserts probabilistic rules to optimize the methods by assigning a fitness value for each method. However, mathematical computation becomes time consuming with the increase in segments and the number of methods. For example, there are 45 solutions containing two methods when the pair-wise comparison is used. For three methods, there are 75 solutions; likewise, the number of solution set increases with the number of methods. On the other hand, GA follows a uniform procedure that is independent of the number of methods. This procedure is not only iterative and generates quick optimum solution, but is easy to code and decode for running the algorithm.

Furthermore, the GA proposed in this work offers the flexibility to handle real-life complexities associated with construction activities. For example, while unit cost was assumed to be fixed in the above example, in reality, unit cost tend to decrease with total length of installation, as mobilization costs, demobilization costs can be spread over a larger number of feet. Thus, the GA can be given two unit cost values per linear feet, one for short distances (say up to 1000 ft) and one for larger total distances (e.g., over 1000 ft). Alternatively, the relationship between unit cost and distance can be express as a mathematical function. Thus, the optimization process now becomes a highly dynamic exercise, with complex constraints. This level of complexity is very difficult to duplicate using a simple pair-wise comparison.

CHAPTER 4

Social Cost and Carbon Cost

4.1 Social Cost

4.1.1 Background of Social Cost

Social costs consume resources, diminish productivity, decrease value, and can cause traffic delays, decrease in property value, and deteriorate eco-systems. However, the use of trenchless methods can reduce the social cost significantly. A study conducted by Matthews and Allouche (2010) showed that trenchless projects can result in a significant reduction in social costs compared with open-cut construction. Traffic delay plays a key role in social costs accounting for 50% of their total monetary value. Trenchless methods not only reduce traffic delay but also result in major savings in other social cost categories compared with trenching methods.

Costs associated with construction projects can be classified into four categories, namely 1) direct costs, 2) indirect costs, 3) social costs, and 4) carbon costs (Figure 4.1). Direct costs is associated to the purchase of material, equipment, and labor payment, whereas the indirect cost is mainly the cost for administration, management, and overheads. Social costs are generated from the negative effects of construction such as noise, air pollution, traffic delay, and business losses. Social costs are borne by the community, not the contractual parties involved in the construction processes (Allouche & Gilchrist, 2004). The carbon cost is discussed in chapter 4.2.

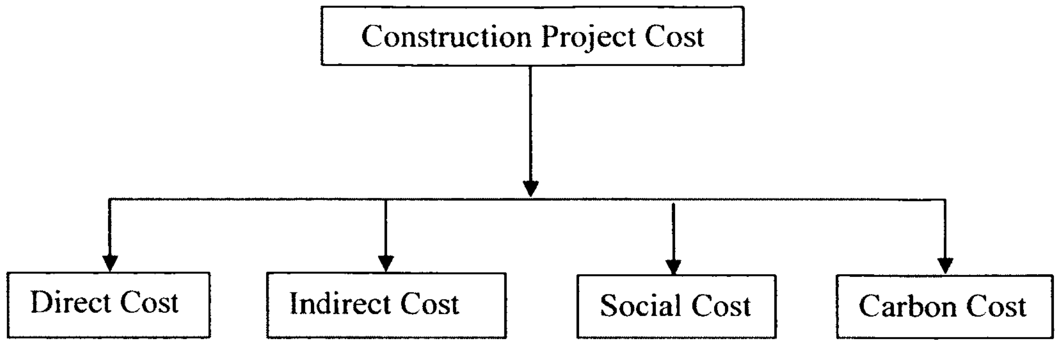


Figure 4.1: Construction project cost

Matthews (2010) developed a social cost calculator (SCC) in order to quantify the social costs along with direct and indirect costs, and to provide a more comprehensive cost estimate of construction projects. This SCC involves eight categories of social cost including traffic delays, vehicle operating costs, pedestrian delays, parking losses, noise pollution, dirt pollution, air pollution, and pavement restoration costs.

Tighe et al. (2003) proposed that trenching affects the road surfaces noticeably, trimming down approximately 30% of the pavement's service life. Therefore, greater benefit can be harnessed if this social cost category is calculated and added to the construction project cost.

4.1.2 Social Cost Valuation Technique

Allouche and Gilchrist (2004) incorporated seven valuation techniques for social cost calculation, which is divided into direct techniques and indirect techniques (Table 4.1). The direct techniques included loss of productivity, human capital, replacement cost, and lane closure cost, whilst the indirect cost included hedonic pricing, user delay cost, and contingent valuation technique.

Table 4.1: Direct and indirect techniques for social cost valuation

Direct Techniques	**Indirect Techniques**
1. Loss of Productivity	5. Hedonic Pricing
2. Human Capital	6. User Delay Costs
3. Replacement Cost	7. Contingent Valuation Technique
4. Lane Closure Cost	

The choice of construction methods greatly affects the services and production of goods. The loss of productivity (LOP) of trenching project depends on the hourly output of employees, their number, time of construction, and a productivity reduction factor (PRF). PRF provides different values for different sectors. For example, the PRF value increases with the increase of noise level (dB) in noise pollution. Various private and public sources supply average hourly output data. The number of employees affected and the duration of the projects are directly multiplied and contribute to the loss-of-productivity.

Human capital factor concerns income loss and health issues associated with traffic delays and construction. This affects the human productivity rather than the production of goods. For example, health threats, environmental quality, loss of jobs, construction accidents, and business loss are the factors that influence human productivity. Human capital is a modified form of LOP, since it counts the change in productivity for people. For large, long-time construction projects, the human capital loss in productivity can be significant, if not properly addressed.

Replacement costs occur due to the replacement or restoration of structure which is damaged. However, this cost can be set at a minimum by choosing the most suitable methods among the alternatives for restoration. There is greater benefit by eliminating trenching methods (e.g. open-cut) and selecting a suitable trenchless method for pipe rehabilitation. Otherwise, it will cost more to restore the surface of open-cut as well as resulting in longer travel distance for motorists to take detours due to construction.

Lane closure cost is a combination of direct and indirect cost that includes cost of traffic delays and control. The typical range of lane closure cost varies between $1000 to $25,000 per day based on the traffic volume and nature of the project (Allouche & Gilchrist, 2004). However, this cost increases with the increase in the number of factors. Each additional factor such as business and economic loss contribute more to lane closure cost.

The price of properties is affected by the surrounding pollutants and traffic factors. Generally, the value of properties in the affected area is lower than the value of properties in the cleaner and safer area. Basically, hedonic pricing deals with these aspects of property prices associated with the pollutants and traffic. The aesthetic context of the properties is also included in hedonic pricing.

User delay cost is based on the delay in time a user experiences due to congestion and obstruction in the areas affected by construction activities. The cost for this delay can be as high as $ 100,000 per day.

Contingent valuation technique

Contingent valuation technique is a method that involves the user's willingness to pay for a service. This service is for the positive social and environmental impact that the inhabitants want to pay for. However, this evaluation is very subjective since the price to pay for this service varies from person to person. Therefore, the data collected from "willingness to pay" surveys must be carefully structured and analyzed.

4.1.3 Case Studies Summary

The social cost data associated with an open-cut and trenchless construction project was collected from five case studies reported in Pucker et al. (2011) and sewer pipeline renewal in City of Troy, Michigan (Hashemi et al., 2008). Case study projects were conducted in various countries such as the United States, Austria, Italy, and Belgium. The trenchless methods applied were micro-tunneling, segmental lining, relining, and pipe bursting rehabilitation. Among the manifold information, only the social cost values are summarized for further cost-comparison. It is found in all six studies that the social cost of the open-cut method is significantly higher than that for trenchless construction methods for a given project.

A sewer replacement conducted in Belgium revealed that the social cost due to the open-cut method could be as high as $3,508,403, whereas a trenchless method cost is only around $607,609. Moreover, the bar-chart (Figure 4.2) demonstrates a robust difference between the open-cut and trenchless method whereas the social cost of the open-cut method results in greater values. Furthermore, it is observed from (Figure 4.3) that utilizing trenchless methods can reduce the project's associated social costs by a factor of 5 to 17.

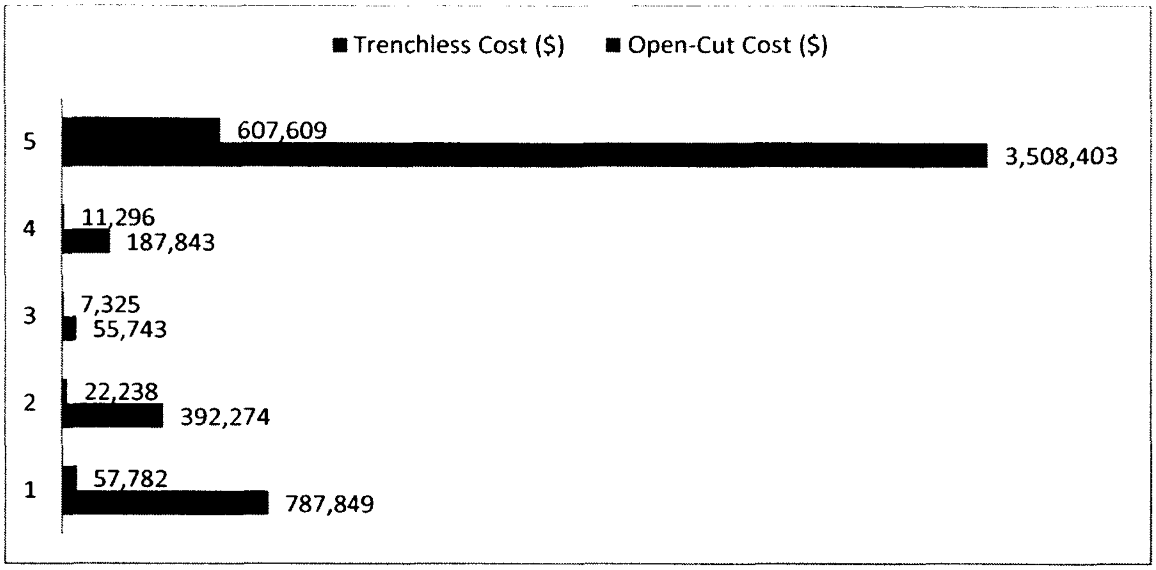


Figure 4.2: Social cost associated with trenchless and open-cut methods

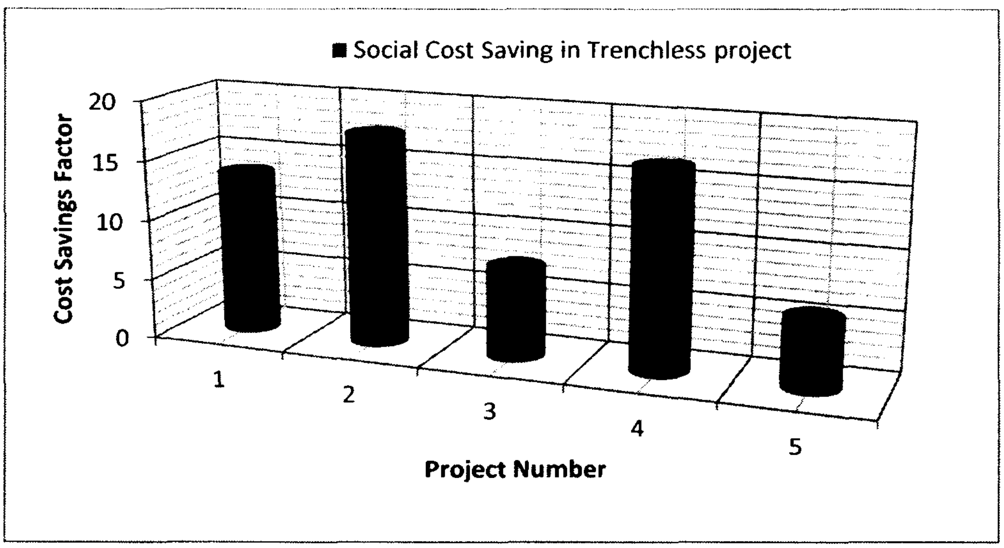


Figure 4.3: Social cost savings using trenchless methods

4.1.4 Social Cost Software Development

A social cost calculation software was developed at the Trenchless Technology Center (TTC) to calculate social costs associated with trenchless projects. The home page of the software (Figure 4.5) is divided into four main tabs, namely a) traffic delay and vehicle operating cost, b) parking loss and pavement restoration, c) noise pollution and air pollution, and d) dirt pollution and loss of business revenue. Each of the tabs is connected to another window that open the specific calculator named on the tab. The calculators typically provide costs for both trenchless and open-cut methods.

4.2 Carbon Offset

The natural environment is one of the key concerns in development projects, and pollutants related emission can affect the environment to a great extent. The "Kyoto Protocol" provides a framework minimizing carbon emissions worldwide. Construction industry is a large contributing source of carbon emissions. Hence, the calculation of CO2 savings is a consideration with the growing importance in the selection of construction methods and equipment.

4.2.1 Carbon Cost Calculator

There are several carbon cost calculator reported by Sihabuddin and Ariaratnam (2009) for the calculation of: a) aircraft emissions, b) individual's home or office, c) automobile, and d) type of vehicles. However, one of the prime focus in this study was to use a calculator that can address the amount of CO2 savings associated with trenchless construction method when compared with traditional open-cut techniques. In this regard, the North American Society for Trenchless Technology (NASTT) developed an online carbon calculator (http://www.nastt.org/carboncalculator). This tool was adopted with several modifications for the calculation of multi-segment optimization.

4.2.2 Carbon Cost Calculation

The calculator is divided into three sections, namely a) Project description, b) Project input, and c) CO2 output (Figure 4.4). The first section requires the user to input general information about the project. The input section of the website has a long list of parameters that is to be supplied by the user. Once the inputs are provided, the calculator generates the output in terms of total CO2 emissions. Furthermore, the output also delivers the amount of CO2 savings for different trenchless methods.

http://www.nastt-bc.org

Project Description:

Title	Segment 2
Location	
Number	2
Company Name	Tech
Your Name	Ashik

Input:

surface	asphalt
asphalt depth (m)	0.0508
length of section (m)	75.6
diameter of pipe (m)	0.5334
depth of backfill (m)	0.1
depth of bedding (m)	1
dewatering (0/1)	0
number of pumps	
Daily traffic	10000
Traffic control days required	3
Times (hours)	
site to plant	1
site to dump	0.5
dump to depot	0.5
depot to site	0.5
Fuel Efficiencies (litres/day)	
small excavator	70
medium excavator	120
large excavator	200
loader	80
roller	120
truck (litres/hour)	10

CO_2 Output Open Cut (tonnes):

CO_2 emissions - traffic	12.7382

Figure 4.4: Sample input carbon offset calculator.

CHAPTER 5

Fuzzy Logic Theory & Analysis of Likelihood

5.1 An Overview of Fuzzy Set Theory and Fuzzy Logic

5.1.1 Background

A fuzzy set contains a class of objects with a corresponding membership value (Zadeh, 1987; Schmucker, 1984). Each object is defined by a membership value ranging between zero to one, where one means complete association and zero indicates no association. The objective class "young" can be ranked with different membership values. As an example, age 20 is associated with a membership value of 1, age 30 with a membership value 0.75, and age 60 with a membership value of 0. Therefore, all the people in this class are "young" to a certain degree. Thus, a fuzzy set would create a universe of discourse for all possible ages.

Another example of a fuzzy set theory consists of a class of "tall men". The tall men are designated to different degrees of membership values between 0 to 1. For instance, men taller than 7 feet have a membership value of 0.95, men taller than 5 feet have a membership value of 0.70, men taller than 3 feet have a membership value of 0.35, and men shorter than 3 feet have a membership value 0.15. A fuzzy set can be expressed graphically by plotting the height of men vs. their membership value (Figure 5.1).

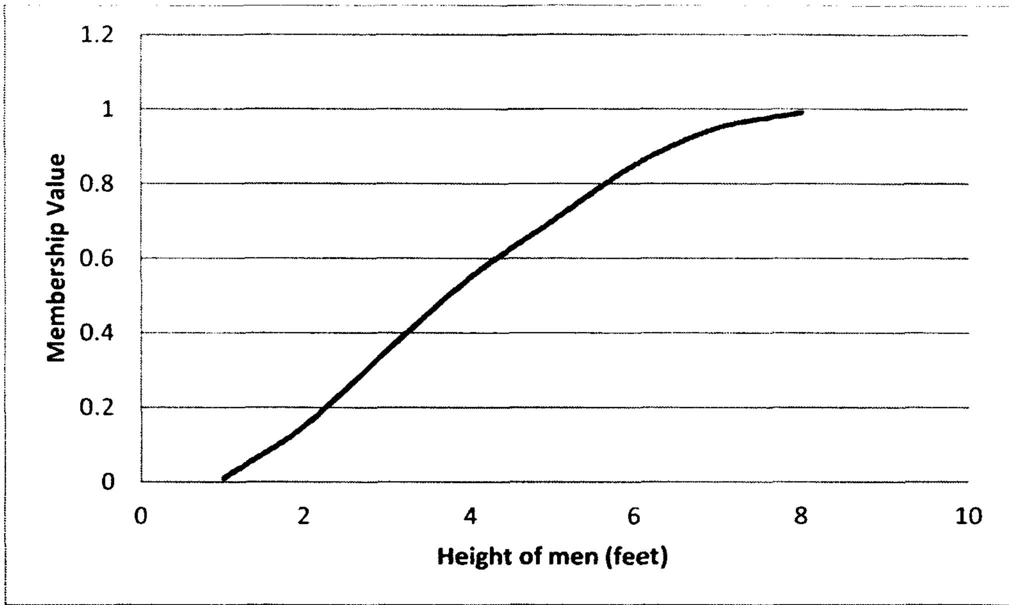


Figure 5.1: Height of men with membership value

The vagueness or fuzziness occurs when the boundary of the problem is not clearly defined or the problem is "ill defined" in contrast with the classical set theory. The classical set theory operates on a binary mode and set the object elements in the form of "yes" or "no". However, in many cases, there is a degree of fuzziness, ambiguity, imprecision, and/or vagueness in the element sets. The objective of the fuzzy set theory is to aid the classical set theory by providing gradual assessment through membership values for the element class. Albeit, the membership value seems similar to probability density, the fuzzy truth is not a likelihood of some event or condition, but rather, it assigns some membership values to imprecisely defined element sets.

Fuzzy logic, derived from the fuzzy set theory, is a combination of four basic steps, namely (1) fuzzification, (2) fuzzy inference, (3) fuzzy rules, and (4) defuzzification. These four steps constitute a fuzzy logic flow chart (Figure 5.2). Fuzzification begins by converting the input data to fuzzy values using membership functions. This is a mathematical procedure and the membership functions can spread simultaneously in the boundary of multiple sets. There are different shapes (Harris, 2000) of membership functions, including:

- Triangular
- Trapezoidal
- Singleton
- Gaussian, and
- Piecewise linear

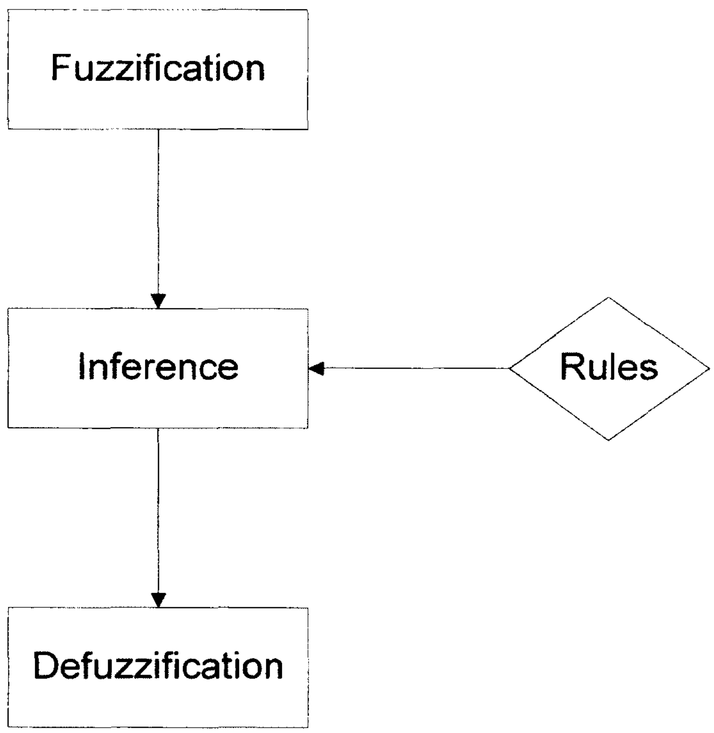


Figure 5.2: Fuzzy logic flowchart

Fuzzy inference evaluates the rules (in the rule base) as well as combines the results of each rule. The individual rules can be combined in different ways such as (a) maximum algorithm, (b) bounded sum algorithm, and (3) normalized sum algorithm.

Fuzzy rules are used to control the output data of a fuzzy logic system. A fuzzy rule consists of an IF-THEN statement. The fuzzy rules set the boundary conditions and provide the ultimate conclusion through output variables. Often, it utilizes expert opinion to link between input and output variables.

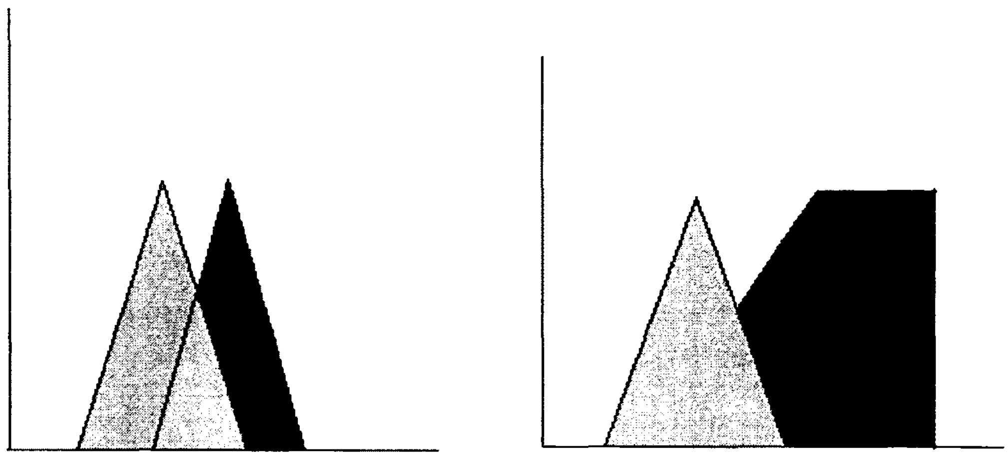
Defuzzification starts after getting all the fuzzy values, and normally is performed according to the output variables. Some of the defuzzification algorithms are a) left most maximum, b) right most maximum, c) center of gravity, and d) center of gravity for singletons.

5.1.2 Fuzzy Mathematics and Defuzzification

Fuzzy mathematics include the following standard operations (Schmucker, 1984; Kaufmann & Gupta, 1985):

- Union
- Intersection
- Complement
- Equality
- Inclusion

If A and B are two fuzzy sets in the X space, then the union of A and B (AUB) is the smallest set that contains both A and B. the intersection of two fuzzy sets A and B (A∩B) means that both A and B sets are included in the operation. Complement of a fuzzy set A is represented by Ac and may not belongs to set A. Equality means two fuzzy sets A and B are equal (A=B) and belong to the same space X. Fuzzy set A is included in the fuzzy set B, if and only if all the elements in the X space have $A(x) \leq B(x)$. The union and intersection of the fuzzy set is presented in Figure 5.3.



(a) (b)

Figure 5.3: Fuzzy set operations (a) intersection, (b) union

Defuzzification is the final step in the fuzzy logic process. Fuzzy sets created by inferences through fuzzy rules assign a different number for different sets. However, all these sets must be combined into a single numeric value as the outcome of the model. Therefore, every fuzzy model has a defuzzifier based on a mathematical formula. If the outcome is more than one, then each outcome is calculated separately but in the same fashion. There are various types of defuzzifier algorithms suitable for different circumstances.

5.1.3 Fuzzy Set Theory to Capture Uncertainty

Uncertainty arises when there is a lack of information or vagueness in knowledge. The concept of uncertainty deals with this lack/missing information which limits the decision making process. In order to make a good decision, there should be an approach that can measure or estimate the missing information and present it in a quantifiable manner. One way to do this is to calculate the degree of uncertainty through probability and rank the object classes for presentation to the users. However, there is a question on how to measure this degree of uncertainty due to missing information. The value of information is dependent on expert knowledge. Therefore, an expert user can provide a source of information, as well as other expert opinions.

The approach described in fuzzy set theory to tackle the complexity and the uncertainty is based on three features (Figure 5.4), namely (1) linguistic and fuzzy variables, (2) relation between fuzzy variables by conditional statements, and (3) characterization of complex relations by fuzzy algorithms (Zadeh, 1987). The contention is that much of the human thinking is not buried in numbers, but rather it is a set, level, or class of objects (Harris, 2000). In many cases, human tasks consist of an approximation reasoning of available inputs rather than crisp computation. For this reason, an approach based on the fuzzy set theory serves towards capturing the uncertainty.

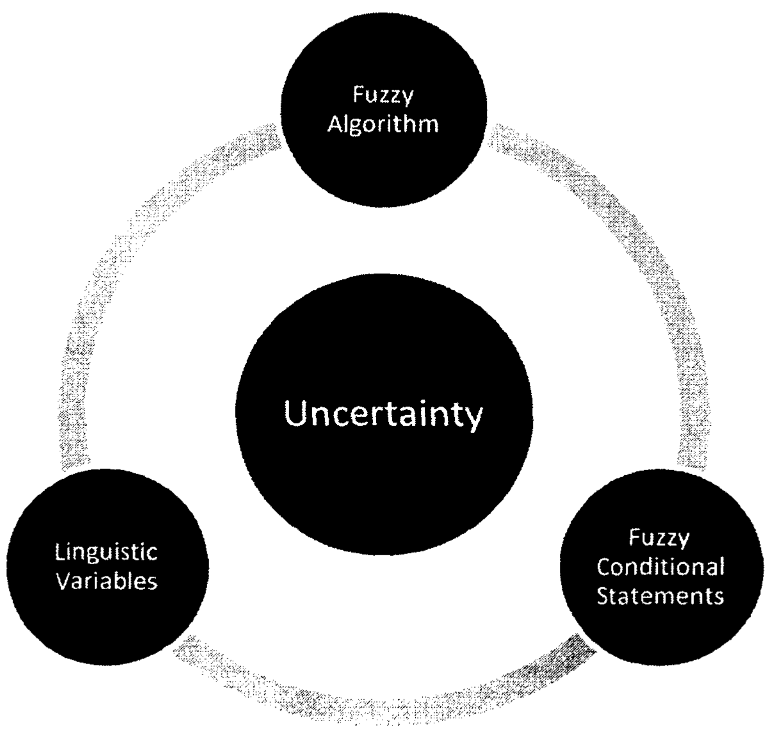


Figure 5.4: Fuzzy theory for uncertainty

Linguistic variables create the system by assigning atomic and composite levels to the fuzzy subsets. For example, if ball F(ball) and green ball F(green) are two fuzzy sets of a set F, then green ball is the intersection of F(green) and F(ball). Likewise, the height of people is a fuzzy variable that can be labeled as not tall, somewhat tall, tall, quite tall, and very tall. The main purpose of a linguistic variable is to provide an efficient method to subdivide a complex problem.

Fuzzy conditional statements depend on available variables and variable interrelation. For example, u and v are two variables related by conditional statement, which can be represented the following way:

If u is small, then v is very big

If u is not very small, then v is very large

If u is large, then v is small

Fuzzy algorithm works as a computer program with ordered sequences and uses the level of fuzzy sets (Zadeh, 1987). For example: Increase the value of u by 0.1 if v is not *very big*, or if u is *very small,* Then stop and increase v by 2.0.

5.1.4 Trenchless Construction Methods

Horizontal directional drilling (HDD), microtunneling (MT), and pipe jacking (PJ) are three widely used trenchless construction methods. The HDD installation process begins with pilot boring, then back-reaming, and end-up with pipe pull-back (Heinz et al., 2004). MT is a remotely controlled guided process that provides continuous support to the excavation. It has four components, namely a boring machine, a jacking unit, slurry circulation, and a remote control guideline system (Park et al., 2004). Pipe Jacking uses hydraulic cylinders to push specifically designed pipes through the ground behind a steerable shield or boring machine (Allouche, 2001).

The trenchless methods considered in this section are Horizontal Directional Drilling (HDD), Microtunneling (MT), and Pipe Jacking (PJ). HDD is a surface-launched system widely used by the trenchless industries for the installation of flexible conduits (HDPE, PVC, Steel, etc.) under rivers or other surface obstructions. A pilot hole is drilled which determines the path of the installed pipe. A small diameter (2” to 7”) drilling string with a steerable head penetrates the ground at the prescribed entry location and a predetermined angle, usually between 8° and 18° (Sterling & Thorne, 1999). The steerable drilling string is pushed through the ground along a pre-determined alignment and returns to the surface on the opposite side of the obstacle. Typically, a back-reamer is attached to the drilling string to cut a tunnel for the conduit to be pulled through.

In microtunneling a remotely-controlled, relatively small diameter tunnel boring machine is used for installing small diameter pipes (<36”). MT provides a relatively lower risk and very accurate alternative for the placement of underground pipes on grades.

Pipe jacking is a steerable mechanical cutting process with continuous manual or mechanical jacking of the pipe. It provides continuous support to the borehole and remove the spoil from the borehole. The boring machine cut the soil in the ground and hydraulic cylinders are used to push jacking pipes through the ground. It is a man entry method which allows personnel entry into the boring machine. Typically, the jacking pipes are fiberglass, steel or RCP, and the diameter ranges between 42" to 120". Pipe jacking is applicable in any ground condition with a higher level of accuracy.

5.1.5 Framework to Capture the Uncertainty in Trenchless Construction

To develop a framework using a fuzzy set theory, HDD, MT, and PJ methods are taken into consideration. The proposed framework addresses a set of input variables based on accuracy (A), difficulties in ground condition (DGC), installation depth (ID), and overall safety (OS). Fuzzification process converts these input variables to fuzzy values using membership function. Fuzzy values corresponding to membership functions are high (H), medium (M), and low (L) (Park et al., 2004). The governing fuzzy rules are IF-THEN condition statements. Based on the fuzzy rules and inference, output variables are determined in Table 5.1. The figure below shows the membership function of the variable "Accuracy" in the case of HDD as a function of insitu soil conditions.

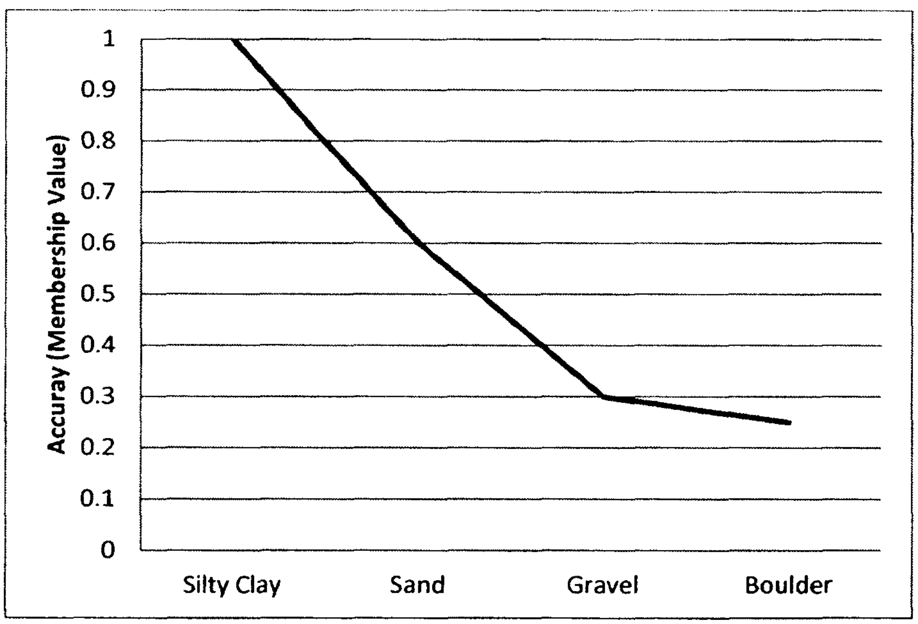


Figure 5.5: Membership function vs. accuracy of insitu soil condition for HDD

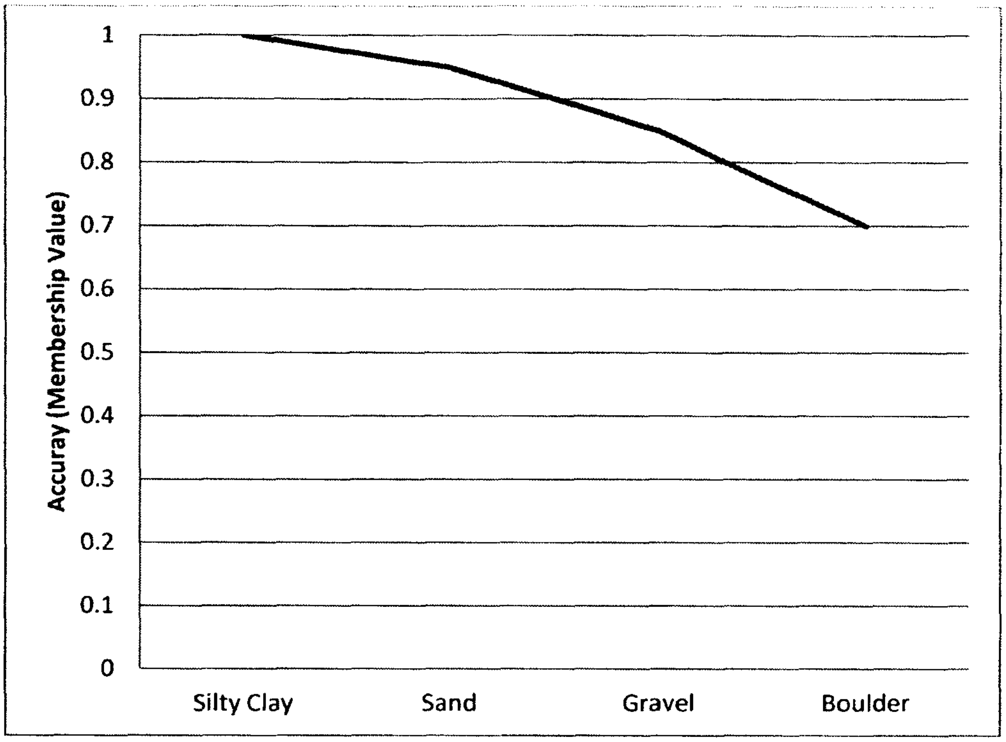


Figure 5.6: Membership function vs. accuracy of insitu soil condition for MT

For example, if the accuracy of construction is medium, difficulties in ground condition is high, installation depth is medium, and overall safety requirement is medium, then the most suitable method based on fuzzy rule is HDD (Table 5.1). Likewise, the selection of MT and PJ is summarized in Table 5.1. The selection of microtunneling (MT) has the following consideration:

IF input = {H, H, H, H} THEN output = HDD{M}, MT{H}, PJ{L}

Table 5.1: Framework for selection of trenchless methods

Input Variables				IF-THEN	Output variables		
A	DGC	ID	OS		HDD	MT	PJ
H	H	H	H		M	H	L
H	M	L	L		M	L	H
M	H	M	M		H	H	L
M	M	M	L		H	M	H

5.2 Software Analysis

5.2.1 Analysis of Likelihood Using Computer Program

This section of the chapter uses a computer program (MATLAB) to apply the concept and framework described in the previous section. A set of input-output variables are addressed in this regard. Fuzzy rules and inference are applied to calculate the likelihood of the output which would be used to compute the ultimate risk score. Particular emphasis is given to trenchless methods that are suitable for new installation.

5.2.2 Input Output Variables

Site condition, geological condition, installing geometry (IG), project contract, and trenchless method are addressed as input variables, as they all contribute to the risk associated with the utilization of trenchless technologies. These five input variables (Table 5.2) are selected on the basis of subjective judgment, and have a greater influence on trenchless installation projects. When the input variables are plugged into the

Mamdani FIS, an overall likelihood of risk for trenchless installation projects can be computed.

Table 5.2: Input-output variables

Site Condition	
Geological Condition	
Installing Geometry (IG)	**Likelihood of Risk**
Project Contract	
Trenchless Method	

Apart from selection and subdivision, the input-output variables are further classified into different categories. For example, input members are classified as poor, average, and good (Figure 5.5), whereas output members are classified as low, medium, and high likelihoods of risks. Here, poor or low indicates the lower bound and good or high indicates the upper bound of input-output variables along the x-axis. In addition to this, input variables have the flexibility of having a different combination of states at the same time. This is elaborated in the scenario analysis Section 5.2.5.

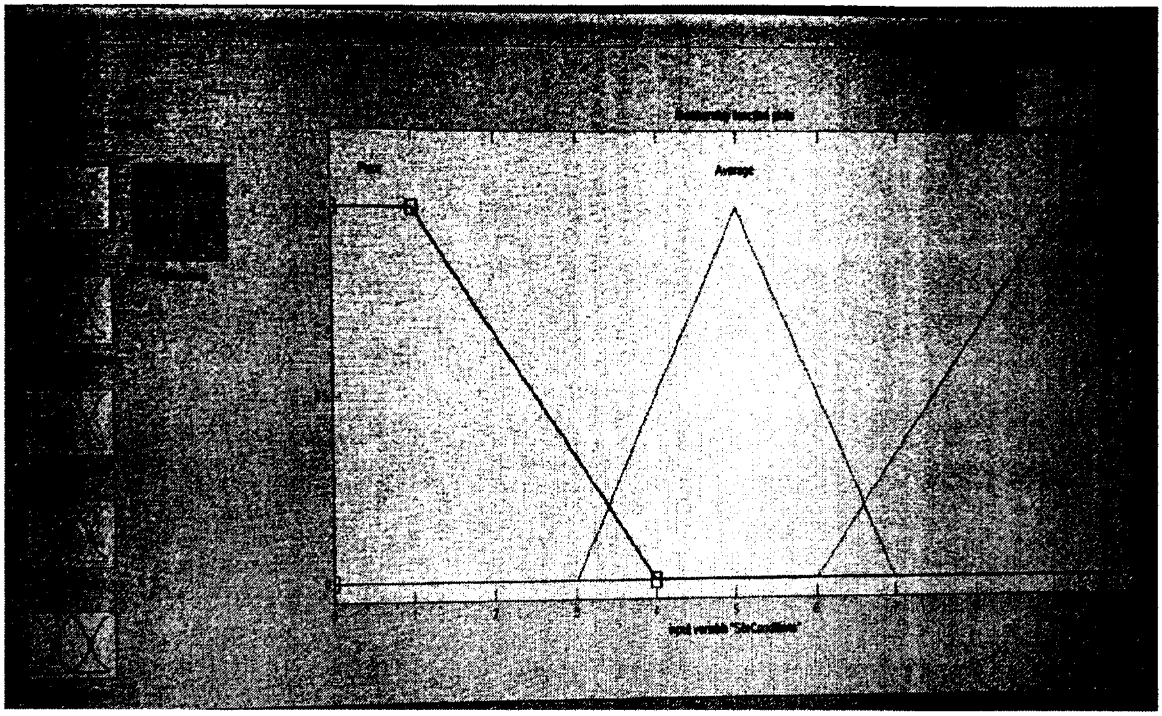


Figure 5.7: Membership function in FIS

5.2.3 Fuzzy Logic for Likelihood of Risk

The fuzzy rules governing the input-output relationship are if-and-then as well as if-or-then. Both of the rules are applied in the Mamdani FIS. Some of the rule base are as followed:

Rule 1: If site condition and suitability of trenchless method is poor, then likelihood of failure is high.

Rule 2: If IG and suitability of trenchless method is poor, then likelihood of failure is high.

Rule 3: If site condition and trenchless method is good, then likelihood of failure is low.

The rules are created with a special emphasis on the trenchless method as it is assumed that if a trenchless method is highly suitable for the project, then the risk will be minimized. All variables are evaluated against the relevant membership function of each variable trenchless method to obtain a final risk score for that method. The developed fuzzy inference model is rationalized by showing that whenever all of the input variables are set for their most likely value, then the resulting output risk score is 3.5 (Figure 5.6).

Figure 5.6 shows that the input variables are interconnected, as well as that overlap exists between different states of input condition. The three trenchless method considered can be assigned to the method input variable depending on project specific requirements. Input members are associated with a scale of 0 to 1 with 10 units, while the resulting likelihood of risk is observed on a scale of 0 to 0.7 with 7 units.

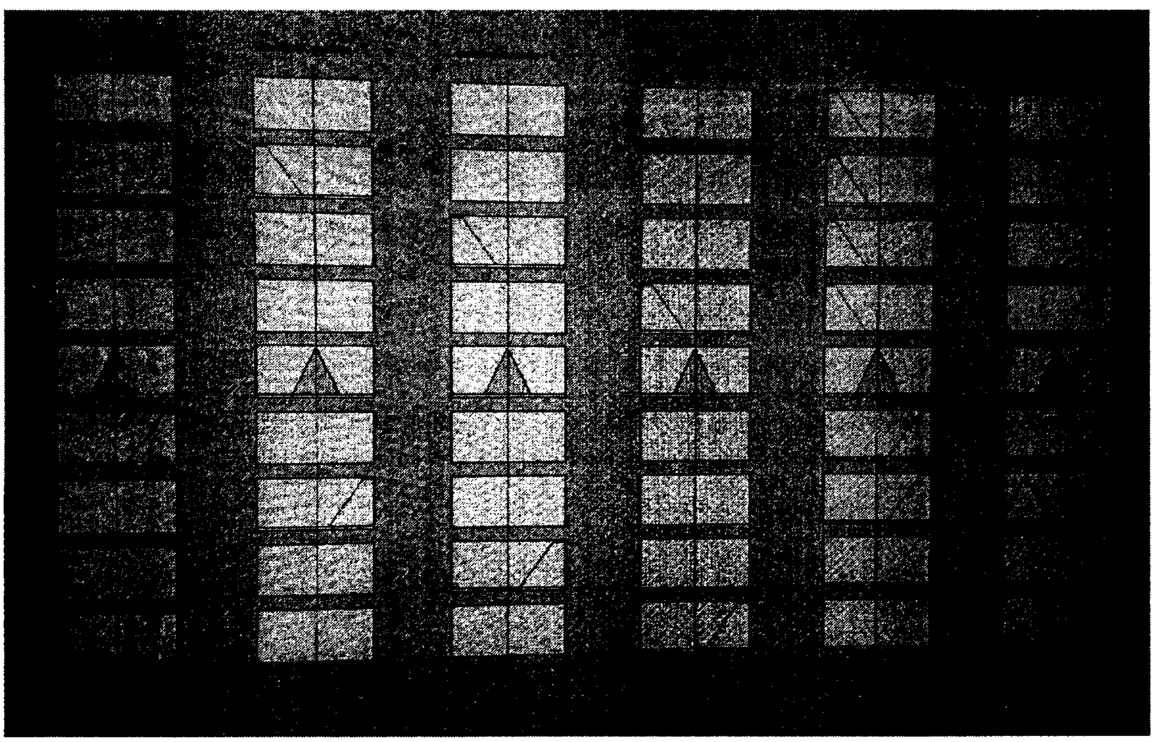


Figure 5.8: Input output relationship in FIS

5.2.4 Scenario Analysis

After creating the rule base in MATLAB FLS (fuzzy logic system) Toolbox, a scenario was analyzed considering the following data set (Table 5.3). The input variables were plugged into the model to generate the output risk likelihood. For example, if the site condition is good, geological condition is average, IG is average to good, project contract is good, and trenchless method technical suitability is good, then the resulting likelihood of risk is 0.25. This value falls in the category of low risk. The overall likelihood of risk associated with a particular trenchless for a given project can be calculated for any given set of input variables using Mamdani FIS.

Table 5.3: Scenario analysis for a given data set

Input				Output			
Variables	Poor	Average	Good	Variables	Low	Medium	High
Site Condition			X	Likelihood of Risk	X		
Geological Condition		X					
Installing Geometry (IG)		X	X				
Project Contract			X				
Trenchless Method			X				

CHAPTER 6

RISK ASSESSMENT FOR HDD CROSSINGS

6.1 Conventional Risk Assessment

Conventional risk assessment begins with the identification of the risks that could be faced during or after the projects. Once the risk factors are identified, it goes through the process of risk quantification and risk mitigation. The basic principle of risk quantification developed in the 1960s, which was primarily based on the concept of likelihood of occurrence and severity of damage. The formula for risk calculation was:

$$Risk = Likelihood of Occurence\ X\ Severity of Consequences \ldots\ldots\ldots (6.1)$$

It was necessary to assess the likelihood that risk will occur and the severity/magnitude of the resulting consequences. The outcome is a risk value/score that could be presented in a risk matrix format (Figure 6.1). The risk matrix shows that the risk score is high towards the lower-right corner of the matrix, and it is low towards the upper-left corner of the matrix.

The next step after risk quantification is the risk mitigation, and mitigation techniques are chosen depending on the risk scores. Therefore, risk analysis should be an integrated part of the project planning and management rather than an isolated activity.

Albeit, conventional approach quantifies risk as a product of likelihood and severity of the outcome, it does not consider the interrelation among different risk input variables. In reality, the input variables are often: a) interconnected, b) over-lapped, and c) fuzzy. It is anticipated that fuzzy logic system, more precisely Mamdani FIS, can overcome these shortcomings of traditional risk quantification process by addressing the interconnection, overlapping, and fuzziness of input-output risk variables.

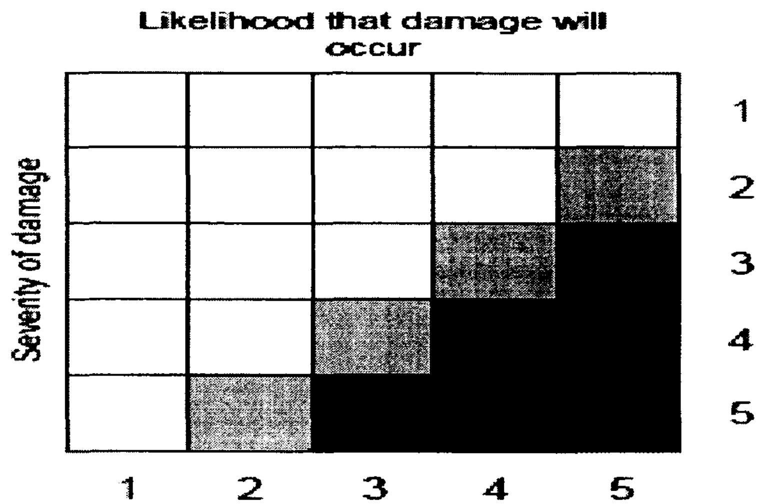


Figure 6.1: Risk matrix

6.2 Validation of the Mamdani FIS Model for HDD

Based on the proposed model, a theoretical framework was developed for the horizontal directional drilling (HDD) method. The framework is assessed by MATLAB software using built in functions, and supplying data from available databases found in the literature. To perform the likelihood of risk calculation, a total number of fifteen input parameters were considered. The input parameters and related logic were captured from HDD projects reported by Osbak et al. (2012). The input parameters for HDD projects are:

a) Frac out (FO)

b) Collapsing soil (CS)

c) Loss of circulation (LC)

d) High annular pressure (HAP)

e) Gauge hole (GH)

f) Stuck in hole (SH)

g) Steering tool failure (STF)

h) Downhole tooling failure (DTF)

i) Unscheduled maintenance (UM)

j) Wait on vacuum truck (WVT)

k) Inspect bottom hole assembly (IBHA)

l) Wait on others (WO)

m) Wait on services (WS)

n) Pilot hole rework (PHR)

o) Flow to exit (FE)

Once the input parameters are inputted to the MATLAB fuzzy toolbox (Figure 6.2), it produces the resulting score in the form of risk value. The fuzzy toolbox shows that there are fifteen input parameters, and only one output parameter, the overall risk likelihood value.

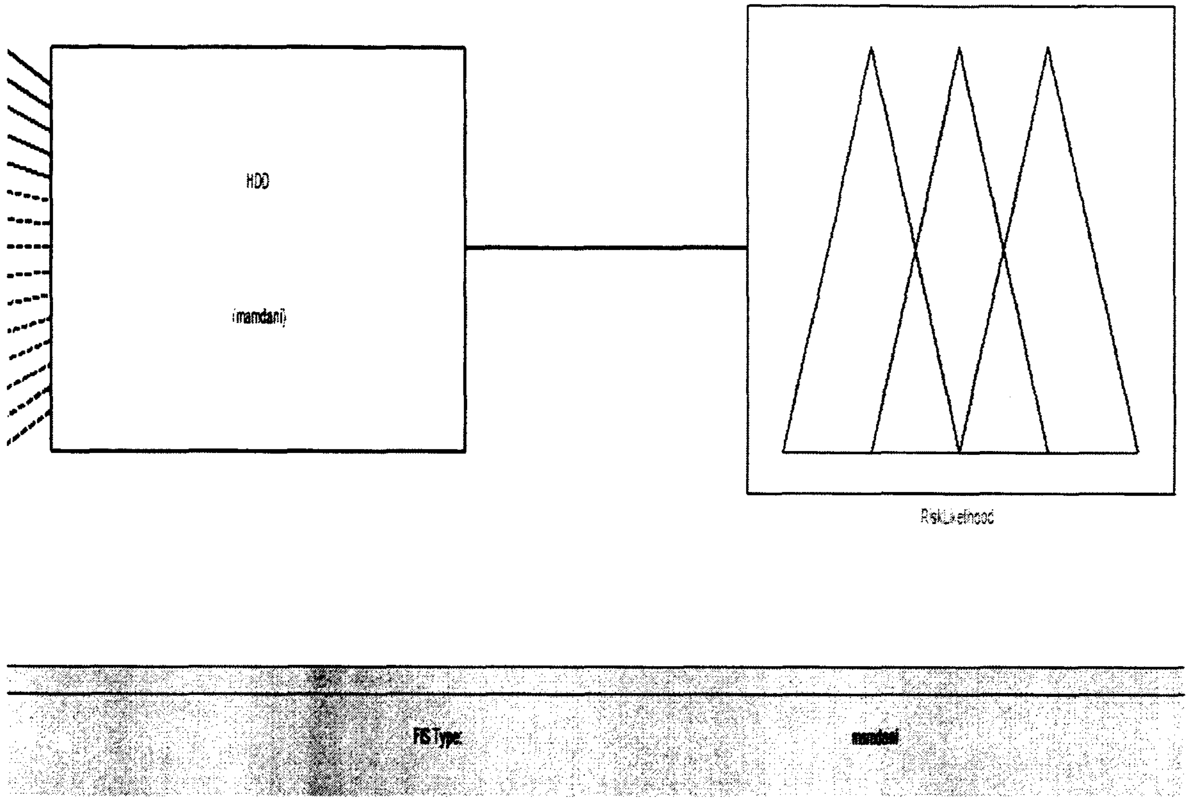


Figure 6.2: Fuzzy toolbox in Matlab

The input-output relationship is realized in Figure 6.3. It shows that whenever all fifteen input variables are medium in value, the resulting risk score is medium. Furthermore, the input-output variables are observed in a scale of 0 to 8.

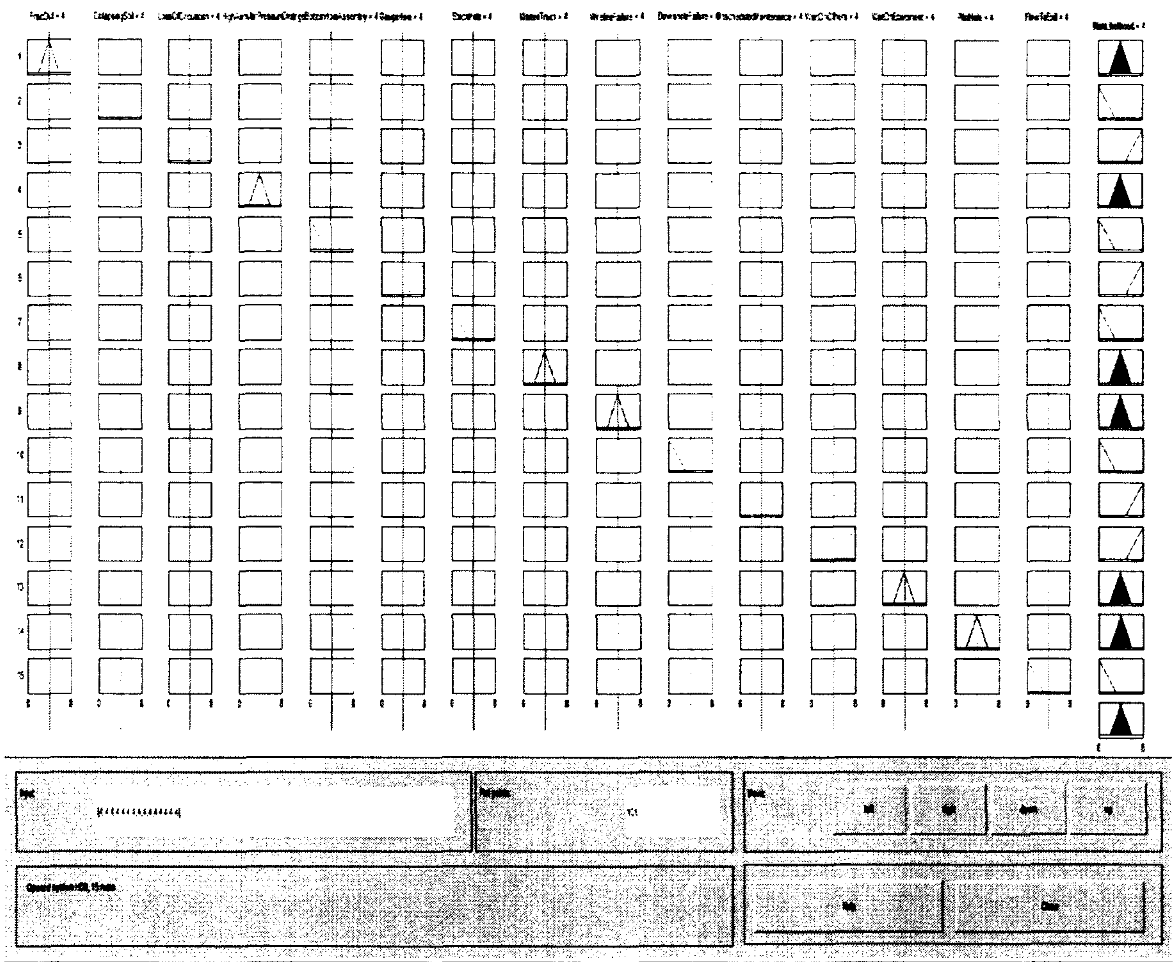


Figure 6.3: Input-output relationship for HDD

6.3 Risk Assessment in HDD

The risk calculation for the HDD method depends on the assessment of subjective factors such as physical condition, geological condition, and safety consideration, and quantitative analysis of one or combination of cost, time, and quality parameters such as cost of installation, duration of construction, and labor rate (Ma et al., 2010; O'Reilly & Stovin, 1996; Ali et al., 2007). In this study a set of fifteen membership functions for HDD are addressed. The interpretation of the membership value is given in Table 6.1.

Table 6.1: Risk associated with HDD

Input Membership Value	Weight Value	Output Membership Value	Weight Value
High	≥ 0.8	High	≥ 0.8
Medium	≥ 0.5	Medium	≥ 0.5
Low	≥ 0.3	Low	≥ 0.3

6.4 Case Study

This case study illustrates trenchless construction of an underground transmission line for city of Vancouver, British Columbia, Canada using horizontal directional drilling (HDD). The length of the HDD was about 2,788 ft along with a 44 inch diameter borehole under False Creek. The product installed included a bundle of HDPE conduits intended to house high voltage electronic cables. The ground condition was seismically stable and the soil type was till-like deposit. There were occurrences of coal and sedimentary bedrock formations. The two trenchless methods considered were Tunneling and HDD. HDD was found suitable due to relatively lower construction cost, low disruption to the environment, and shorter construction duration compared with tunneling. The bundle consists of six High Density Polyethylene (HDPE), with a diameter of 4.5 inches each. A diligent public relation was maintained althrough the project by implementing an emergency service response, advanced notification of closure, and a 24 hour shuttle bus service.

Table 6.2: Summary of technical information

Utility Type	Electric Transmission
Type of Construction	New Alignment with Open cut
Length of Construction	2788 ft.
Diameter of Construction	44 in.
Depth of Cover	32 ft.
Alignment Accuracy	High (Maximum Deviation +/- 4 in.)
Profile Accuracy	High (Maximum Deviation +/- 4 in.)
GWT Depth	Not Available
Pipe Materials	HDPE and PVC
Soil #1	Till-like deposit (50%)
Soil #2	Bedrock (25%), Sandstone (25%)
Allowable Extent of Excavation	Continuous
Site Accessibility	Very Limited (Beneath Creek)

6.4.1 Mamdani FIS for HDD Case Study

The site condition of the case study projects demonstrated that there were till-like soil deposit and loose rock, siltstone, sandstone, along with local sedimentary bed rock and coal. Therefore, a set of membership functions was chosen to be used in the MATLAB fuzzy logic toolbox (Figure 6.4). The membership value are classified as high, medium, or low based on the project's specific conditions as given in Table 6.3. The project was a high priority project.

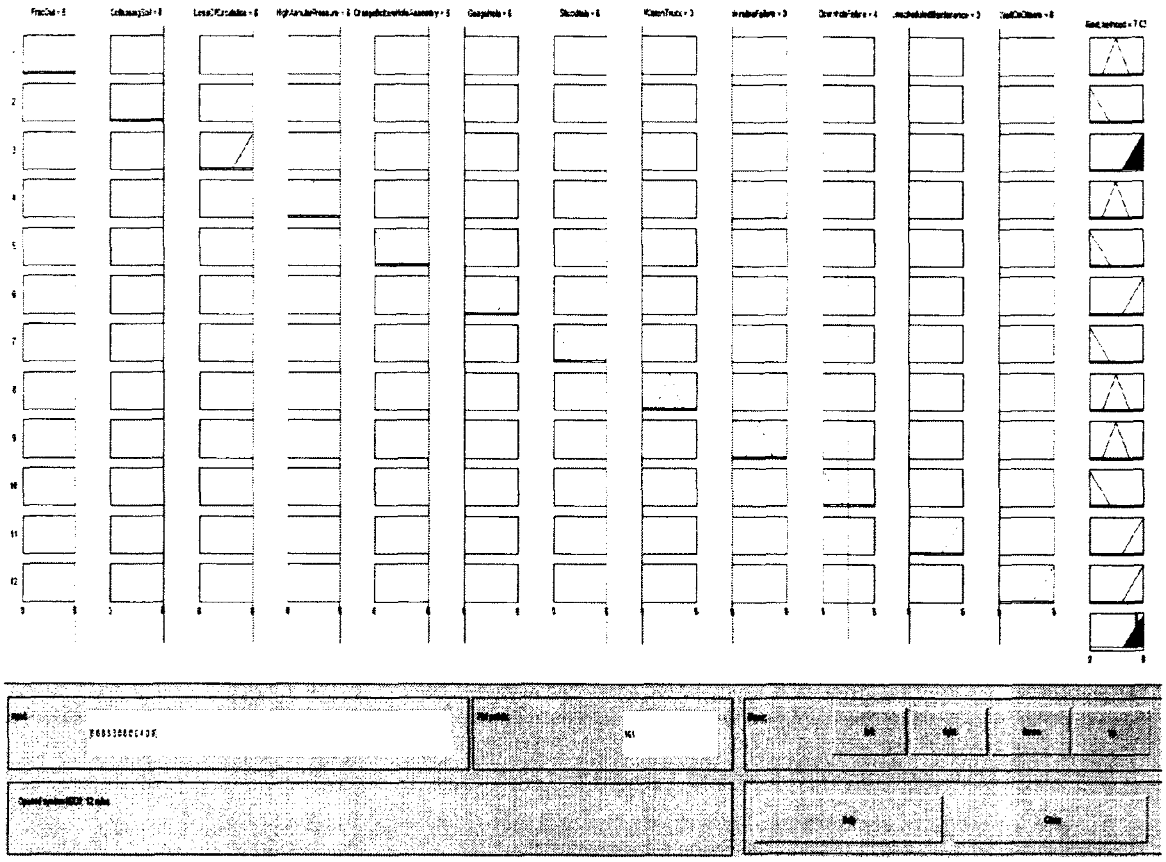


Figure 6.4: Mamdani FIS analysis of HDD

Table 6.3: Risk scoring for a HDD project

Membership function	Membership Value	Explanation	Output Risk Value
FO	High	Loose rock formulation/organic inter bedding	High
CS	High	Loose rock formulation/organic inter bedding	
LC	High	Loose rock formulation/organic inter bedding	
HAP	High	Loose rock formulation/organic inter bedding	
GH	Low	Organic interbedding/loose formulation	
SH	High	Unstable formulation	
STF	Medium	Cobbles/Boulder	
DTF	Medium	Cobbles/Boulder	
UM	Low	Cobbles/Boulder	
WVT	Low	On-site Unit	
IBHA	High	High probability of Borehole assembly failure	
WO	Low	High priority project	

6.4.2 Risk Score from TAG-R

The technical input information for TAG-R was summarized in Table 6.4. It was a transmission line construction project under a very difficult site condition. There were multiple soil formations along the path of the pilot bore. Continuous excavation was needed for the installation of HDPE pipe. The TAG-R result shows two technically viable methods with a corresponding risk value (Figure 6.5). The only technically viable trenchless method was found to be HDD Maxi and corresponding risk value was determined to be very high. This is in good agreement with the findings of Mamdani FIS risk value.

Figure 6.5: TAG-R result for HDD

CHAPTER 7

CONCLUSIONS AND RECOMMENDATIONS

7.1 Summary

GA produces an efficient solution to the problem associated with the optimization of multi-segments, yet its application requires rigorous study and research to reap a greater benefit. Furthermore, the complexity of mathematical calculation increases significantly with an increase in the number of methods and segments. The procedure described in this paper follows the basic flow chart of GA from initial encoding to final decoding of the solution. The utilization of a GA algorithm provides a resource efficient approach for considering variables in the bid price such as the impact of mobilization and demobilization costs as well as the impact of economy of scale.

This work proposes a novel approach towards the analysis and assessment of risk associated with the installation of trenchless technologies using the fuzzy logic system model. The fuzzy logic based approach is further reinforced by the governing fuzzy rules as it allows the application of expert knowledge in the decision making. Therefore, it could serve as an integrated part of the decision making process to augment traditional risk assessment techniques.

7.2 Conclusions

The following conclusions are made based on the research work presented in this dissertation:

1. GA follows a uniform procedure that is independent of the number of methods. This procedure is not only iterative and generates a quick optimum solution, but also it is easy to code and decode for running the algorithm.
2. Using a GA based approach the complexity associated with cost estimating of buried infrastructure project can be explicitly accounted in the method optimization selection process, e.g. unit cost can be defined as function rather than constants.
3. Mamdani FIS addresses the fuzziness, interconnection, and overlapping of different input variables and computes an overall risk output for a given scenario, which is beyond the scope of conventional risk assessment.
4. The utilities and owners can harness a fruitful benefit when evaluating the risk of proposed trenchless projects by using the model and software described in this dissertation for risk quantification.
5. Although the proposed approach is utilized for MISO risk analysis only, it can certainly be used for the multi-input multi-output (MIMO) risk assessment as well.

7.3 Recommendations

Recommendations for future research are as follows:

1. The optimum method selection produced by GA should be codified into software and integrated with other pre- and post-rehabilitation assessments, the structural condition of the pipe, and the carbon offset from the machineries and equipment being used.
2. The multi-segment, multi-criteria approach add capabilities for adjusting costs as a function of the total length for a given method as well as schedule/duration.
3. The fuzzy logic theory and analysis of likelihood is validated for the risk assessment in HDD projects. The theory and procedure described in Chapter 5 and Chapter 6 can also be utilized for other trenchless methods such as microtunneling, pipe bursting, and pilot tubing.
4. Mamdani FIS could be a basis for risk comparison with other available risk models such as Seguno FIS or Monte-Carlo risk simulation.

APPENDIX A

EXPERT SYTEMS IN DECISION MAKING

Expert systems use human intelligence and knowledge to solve the problems. Based on the knowledge base, a set of data and rules are developed which are then applied to the computer. However, the conventional programs are suitable for solving specific problems through conventional logic. Solution to versatile problems require an expert level program, where the logic may evolve as the human know-how for up-to-date decision making. This means solving different problems without re-programming. Books and journals are a great source of knowledge a human can go through and gather information from. The essence of the expert system is to entail similar knowledge that substitutes human intelligence while demonstrating excellent decision making.

Expert systems generally consist of shells that can gather and store necessary information. However, the information should be entered using specified data structures such as data, objects, strings, hypertext, and interfaces connecting internal-external databases. The programs are governed by rules that lead to forward or backward chaining. The chaining loops continue running until the rules are satisfied. Once the rules and conditions are established, the expert systems provide the most appropriate result. Albeit expert system shells are computer language, the range of application is not wide open like other programming languages.

The application of expert systems is conceptualized in operation research and in the area of optimization. The advantage of expert algorithms over mathematical optimization techniques is that it can optimize the system globally, whereas the mathematical methods optimize mostly locally. There were two categories of expert system depending on the operational mode, namely (1) stand-alone expert system, and (2) tandem expert system (Kusiak & Heragu, 1989).

The stand-alone system entails a simple procedure based on data and logic related to specific problem. In many cases, this system fails to provide the optimum solution to a given problem, because of the lack in use of heuristic algorithm. Heuristic algorithm could combine the quantitative as well as the qualitative aspect of the problem to identify the optimum solution.

Tandem expert system is shell based, connecting database, models, and algorithms. Therefore, it can modify the data and models, and pick the most suitable algorithm to find the most suitable answer. If the existing model is not sufficient, then the system constructs the model. The solution developed by the algorithm is checked and modified to integrate the qualitative part. Three variants of tandem expert system are as follows:

1. Data modifying expert system
2. Model based expert system
3. Model modifying expert system

Data modifying expert system works on data generation and data reduction. These data are utilized by expert systems to support the problem solving process. Typically, a suitable model is selected to incorporate the data collected by an expert system from an external source or the system can generate data where necessary. Furthermore, the system analyzes the data and chooses a proper algorithm to enhance the problem solving process.

Model based expert system uses a number of models and establishes one model for each specific situation. The model changes to comply with the change in boundary condition and situation. The objective of a model expert system is to pick the most appropriate model for a given circumstance. However, the evaluation of the model and solution of the problem is performed by separate algorithms. The knowledge and data utilized by expert system is guided by rules. For example, a machine layout problem could consists of five classes of rules (Kusiak & Heragu, 1989):

Class 1 rules for determining the type of layout or the type of material handling system

Class 2 rules for selecting an appropriate model and algorithm for the layout problem

Class 3 rules for making initial assignments based on input data

Class 4 rules for varying parameters within the algorithm (if applicable)

Class 5 rules for checking whether the layout is implementable

Model modifying expert system is an advanced step where the system itself can modify the model according to the problem statement and solution requirement. This system not only just randomly uses the knowledge base but examines the knowledge to find out which is most suitable to the problem environment. Generally, the user inputs the problem, and the computer interrelates with a model management system that extracts the best-fit model through a pattern matching technique. Moreover, an algorithm is developed for the model constructed for the problem.

The expert system aids and guides the decision making process in two way. First, it generates several alternative solutions to the problem. Second, the alternatives are evaluated and ranked according to their performance. Lan et al. (2005) suggested that a decision support system can consists of four sections:

1. A database that contain various prototyping processes
2. An expert system to determine various alternatives based on its knowledge bank
3. A fuzzy synthetic evaluation model to choose the most suitable prototype
4. Interfaces for the user and expert to interact with the system.

The above four sections can work together to develop a complete decision making task. Here, the task of the expert system is to generate feasible alternatives, and present them to the unskilled users. The system not only demonstrates expert knowledge to the inexpert users, but also guides them to the assessment of alternatives. The rules are primarily established on the condition of IF, THEN, and ELSE statements. Information collected from various sources is stored in a database such as MS Access, MySQL, or Oracle.

The overall operation could be integrated in a software to create a web-based expert system. A JAVA based expert system shell JESS mainly functions on forward chaining loop is a useful tool for the decision support system. However, the success of an expert system is very much buried in the feedback and interaction of the user. Therefore, it is essential to select software that is user-friendly as well as guide the user towards a fruitful result.

JESS is an open source software, yet powerful rule engine, and equally applicable in a stand-alone or web-based environment. Because of its access to the XML format, gathering knowledge from the Internet becomes easy. Therefore, many expert systems conceptualized JESS as a central development tool. There are two key components of JESS knowledge-base, namely (1) rules, and (2) facts. The purposes of rules are to set the facts according to logic, whereas the facts mean a true piece of information. Furthermore, facts are classified into three categories (Jovanovic et al., 2004)

Ordered facts: Ordered facts do not contain any predefined structure.

Unordered facts: Unordered facts contain frame or templates in its construction.

Definstance facts: Definstance facts are Java class based and depends on user defined instances.

Genetic algorithm is a form of artificial intelligence, aids the optimization in decision making, and improves the solution of optimization problem (Malkawi et al. 2004). For the optimization of the design decision, it adapts generate-and-test approaches which basically synthesize and evaluate the design process simultaneously. Here, the optimization appears from the continuous iteration of searching to find the best possible decision. Moreover, the total system works inside a framework that includes a set of goals and circumstances for optimum decision making.

The advantage of GA is that it can run by parallel processing. If the strings's structure is break-down to individual strings, the task can be done individually and in parallel at the same time. In this way, multiple processors are applied to conduct concurrent searching and processing of the job. This reduces the run-time of the program significantly, as the addition of more and more processors would lessen the time linearl

APPENDIX B

TAG-R ANALYSIS OF SEGMENTS

B.1 Segment #1

The input required by TAG is summarized in Table B.1.

Table B.1: TAG input parameters for Segment #1.

Utility Type	Sewer
Condition	Lacking Hydraulic Capacity
Length of Host Pipe	280 ft.
Host Pipe Diameter	8 in.
New Pipe Diameter	12 in.
Depth of Cover	22 ft.
Accuracy Needed	High (Maximum Deviation +/- 4 in.)
Depth to Ground Water	14 ft.
Host Pipe Material	Vitrified Clay Pipe
New Pipe Materials	PVC and Reinforced Concrete
Soil #1	Firm Clay (50%)
Soil #2	Stiff Hard Clay (50%)
Allowable Extent of Excavation	Continuous
Site Accessibility	Medium (Residential Area)

TAG was used to analyze Segment 1 using the parameters in Table B.1. Six methods were found to be technically viable. There were three trenchless new installation methods, open cut excavation and two inline replacement methods capable of performing the construction. Table B.2 provides the methods and their associated risk scores.

Table B.2: Technically viable methods for Segment #1.

Method	**Risk Score**	**Relative Risk**
Pipe Bursting	1.38	Very Low
Microtunneling	1.38	Very Low
Pipe Eating	1.57	Low
HDD Midi	1.74	Low
Open Cut	1.74	Low
Pilot Tubing	2.55	Moderate

B.2 Segment #2

The input parameters required by TAG and TAG-R are listed in Table B.3.

Table B.3: TAG and TAG-R input parameters for Segment #2.

Utility Type	Sewer
Condition	Lacking Structural Integrity
Length of Host Pipe	248 ft.
Host & New Pipe Diameter	21 in.
Depth of Cover	23 ft.
Accuracy Needed	High (Maximum Deviation +/- 4 in.)
Depth to Ground Water	16 ft.
Host Pipe Material	PVC
New Pipe Materials	PVC and Reinforced Concrete
Soil #1	Firm Clay (50%)
Soil #2	Stiff Hard Clay (50%)
Allowable Extent of Excavation	Access/Receiving Pits Only
Site Accessibility	Limited (Urban Area)
Deterioration Level	Fully Deteriorated
Cross-Section Reduction	Small (Close-Fit Liner Needed)
Access Allowed	Manhole

Even though risk results are not included in TAG-R, a risk value was assigned to each rehabilitation method based on the algorithm developed for TAG. Since depth parameters are not used in the evaluation of rehabilitation methods, a value of 1 (very low risk) was assigned for this parameter. In a similar fashion, soil data is not used for rehabilitation method evaluation and again a value of 1 was used. The final risk parameter needing special consideration for rehabilitation methods is the environmental impact which was assigned in a similar fashion as it was done for the new construction and inline replacement methods.

TAG and TAG-R software were used to analyze the segment using the above mentioned parameters, and eight construction methods were found to be technically viable. There were three trenchless new installation methods and two inline replacement methods capable of performing the construction from the TAG evaluation. There were also three rehabilitation methods capable of rehabilitating the sewer pipe from the TAG-R analysis. Table B.4 lists the various methods and their associated risk scores. CIPP was considered to be the least risky method for rehabilitating the segment.

Table B.4 Technically viable methods for Segment #2.

Method	Risk Score	Relative Risk
CIPP	1.38	Very Low
Microtunneling	1.74	Low
Folded Pipe	2.08	Low
Pipe Splitting	2.08	Low
Spiral Wound	2.40	Low
Pipe Eating	2.40	Low
HDD Midi	2.98	Moderate
Pilot Tubing	3.94	High

B.3 Segment #3

The input parameters required by TAG are summarized in the Table B.4.

Table B.5 TAG input parameters for Segment #3.

Utility Type	Sewer
Condition	Lacking Structural Integrity
Length of Host Pipe	264 ft.
Host & New Pipe Diameter	12 in.
Depth of Cover	15 ft.
Accuracy Needed	High (Maximum Deviation +/- 4 in.)
Depth to Ground Water	16 ft.
Host Pipe Material	Vitrified Clay Tiles
New Pipe Materials	PVC and Reinforced Concrete
Soil #1	Firm Clay (100%)
Allowable Extent of Excavation	Continuous
Site Accessibility	Medium (Residential Area)

TAG was used to analyze Segment 3 utilizing the parameters listed in Table B.4, with only three methods being recognized as technically viable, two trenchless methods, and an open-cut. Table B.5 provides the methods and their associated risk scores for Segment 3.

Table B.6 Technically viable methods for Segment #3.

Method	Risk Score	Relative Risk
Microtunneling	1.19	Very Low
Open Cut	1.74	Low
Pilot Tubing	1.92	Low

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