Fuzzy Logic-based Economic Model for Water Main Renewal

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ABSTRACT

Drinking water mains are failing at accelerating rates nationwide, leaving managers without robust, consistent, validated tools to prioritize renewal projects in uncertain conditions. The research leveraged empirical pipeline data and advanced modeling technique to address the issue, beginning with the creation of a standard cost data framework developed using nearly 200 industry case studies from over 30 North American utilities. The data standard enabled an economic modeling study of common renewal tactics via life cycle costing and equivalent uniform cost comparisons of competing interventions over time. The modeling was tested through both deterministic and probabilistic methods to reveal the sensitivity of the models to variations/errors in key inputs such as discount rate, project costs, and pipe service life.

Despite these efforts the economic models proved unreliable in accurately choosing the best intervention and timing when compared with best practices as defined by AWWA per the in-situ conditions, seeing only an average 63% match. To overcome the limitations, fuzzy modeling techniques were developed and applied using critical physical, spatial, and economic parameters driving pipe performance (St. Clair, 2015)(Ge 2017). The Type-2 model was trained and calibrated using nearly 37,000 break and advanced condition assessment records collected from participating utilities. The fuzzy model greatly outperformed the deterministic economic decision-making heuristics by achieving an 85% match with best practices in intervention selection and timing.

The dissertation finally provides guidance on the deterministic vs fuzzy modeling techniques for practical implementation, addressing the benefits of integration with GIS for advanced asset management. The

research provides a novel, results-backed approach that enables utilities to make defensible decisions under uncertainty amidst rapidly deteriorating critical water infrastructure.

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GENERAL AUDIENCE ABSTRACT

Across the US, water pipes are aging so fast that it has become difficult to keep the system operating well with limited budgets. Traditional methods choosing which pipes to fix and when often rely on outdated processes that lead to main breaks or replacing pipes too early. This research includes a new model that works well in selecting the right pipes to fix at the best time, even when there is inaccurate or missing information needed to plan properly. The model uses dozens of factors including pipe condition and project costs to select which pipes should be replaced first. The model was developed using nearly 27,000 records of past pipe repairs and inspections, then tested in live workshops with utilities covering the West Coast, Midwest, and East Coast. It accurately matched expert recommendations over 80% of the time, thereby reducing inaccurate project timing by 27% and limiting major pipe failures by 15% when compared to older methods. The findings & recommendations help save money, reduce disruptions, and protect the public and environment by improving decision making on water main repair.

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1. INTRODUCTION AND BACKGROUND

1.1. BACKGROUND AND PROBLEM STATEMENT

The United States' critical infrastructure is in disrepair, particularly its buried municipal water mains; he latest ASCE infrastructure report assigned a grade of C- to water pipelines in North America (ASCE, 2021). Linear infrastructure – namely water and wastewater pipes worth trillions of dollars – is facing an increasingly urgent need for advanced condition assessment and renewal planning (EPA, 2018). Yet, 90% of the pipe being replaced by utilities throughout the nation has not yet reached the end of its useful life (Xu 2022; Xu and Sinha 2019). This reflects the lack of effective models and tools to precisely guide both renewal method selection and the timing. A robust methodology to guide exact renewal project selection and timing is needed to support more effective reinvestment decisions (Allbee, 2008). This study developed an integrated framework of performance modeling and economic analysis to support the most effective management strategy over the planning window.

Figure 1-1. Industry Shortcomings in Water Utility Asset Management

1.1.1. Industry Gaps

Various models and tools have been developed and used to provide informed decision support, yet the industry as a whole is not meeting acceptable performance and financial sustainability metrics. Readily available tools such as life cycle cost development spreadsheets, break-based thresholds for replacement, or deterioration models based on survival curves are often inadequate at supporting effective decision making in that they fail to fully grasp each utility's unique risk exposure and performance requirements.

Additionally, many utilities lack the data necessary to operate the models effectively (Xu and Sinha 2020; Xu and Sinha 2021), and where the data is available, the lack of standardization and collaboration across departments prevents its effective use. Effective data collection and collaborative modeling are essential to the sustainability of the drinking water supply system nationwide.

1.1.2. Contribution to the Body of Knowledge

This research acknowledges and seeks to remedy these shortcomings by developing a novel, robust water main renewal decision support framework. The effort began with the development of a data standard for the parameters essential to asset management decision support fueled by the collection of comprehensive, validated pipe data necessary to develop and implement decision support models from over 200 water utilities in the U.S. The standard allowed advanced modeling efforts due to the large, validated dataset. All data gathered and leveraged in this research was handled as required by the memorandums of understanding signed with the utility participants.

Classic, deterministic economic tools (WERF's Life Cycle Cost Tool & Economic Assessment Spreadsheet Tool) were then tested for their abilities in guiding project selection using the high-quality data. The models alone proved insufficient at handling the uncertainty and complexity of pipe economic performance adequately enough for robust pipe renewal decision support, driving the direction towards a more advanced, adaptive modeling approach. The research then developed a soft computing, Type-2 fuzzy model guided by expert opinion and calibrated via 27,000 repair and remaining wall thickness records. The model was benchmarked by comparing its suggested renewal interventions to project selection as guided by AWWA M28/77 standards, evaluating decision agreement and error. These standards dictate proper water main renewal method and timing based on key indicators such as number of breaks, soil corrosivity, pipe vintage, and the remaining principal drivers of failure. The tuning of the fuzzy model was completed when the model averaged a success rate of 85%. It was then tested on critical utility expert group pipe assets; its outcomes being compared to best practices within the utilities themselves via workshops with the utility managers. These utilities were chosen based on their history of good data collection and advanced asset management programs. Blind testing proved the fuzzy model to be as successful or better in choosing the best project selection and timing for 200 samples, even with advanced ground truth data withheld from the researchers. The economic models were excluded from further research as they could only achieve a 63% success rate under the best circumstances. This research builds on previous efforts by harnessing a large national dataset to allow the collaborative development of data standard and renewal selection tools. An expert committee comprising seasoned utility directors and consultants provided the necessary guidance to achieve the intended success. The resulting models and tools are continuously upgraded and refined within the WATERiD and PIPEiD platforms (Sinha 2013, Sinha 2021), which support the aggregation of pipeline data and collaboration between researchers, utilities, and consultants for the ongoing improvement of management practices and enhancement of water sector knowledge.

1.2. RESEARCH OBJECTIVES

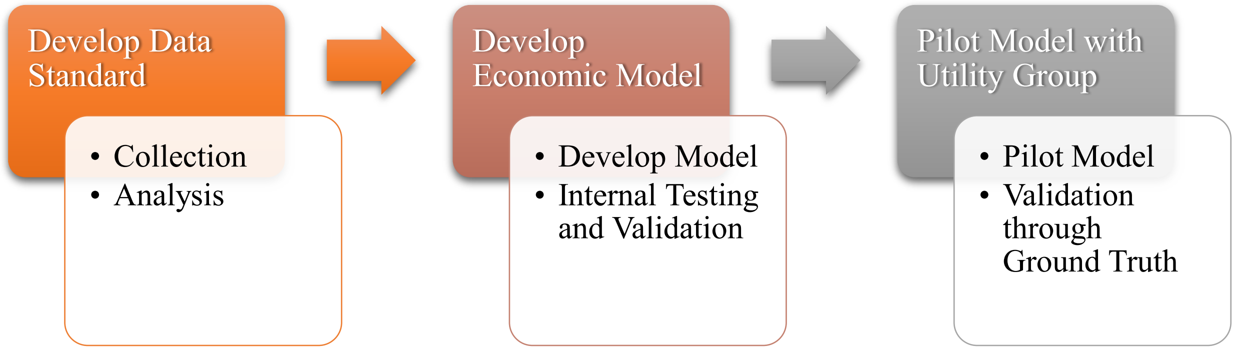

Figure 1-2. Phased Research Process for Water Main Economic Data Standard and Modeling

The research objectives address the critical gap in current water main management practices by:

1. Developing a pipe asset economic performance data standard allowing robust, advanced renewal decision support
2. Benchmark industry economic tools' usefulness in decision support using the superior data
3. Develop and validate a soft computing model that successfully integrates physical and economic performance parameters for renewal decision guidance
4. Explore the new model's abilities to work with GIS to further enhance its utility in everyday real-world use

1.1.3.Dissertation Structure

- Chapter 2 covers a complete literature and practice review, along with the development of the data standard and data collection
- Chapter 3 includes the results of the testing of the economic tools
- Chapter 4 covers the development and testing of the Type-2 fuzzy model.

- Chapter 5 includes the key findings, implications for the industry, and guidance on future work in conclusion.

2. LITERATURE AND PRACTICE REVIEW

2.1. INTRODUCTION AND PURPOSE

This chapter provides the groundwork for the modeling work covered in Chapters 3 and 4 with comprehensive research and practice reviews completed during the research, related to water main data collection and use, pipe inspection and renewal technologies, and finally the models and tools available (and unavailable) but essential to successful management. The purpose is to identify the principal shortcomings of current industry practices such as incomplete information, lack of training, and reactive pipe interventions that create the challenges utility practitioners currently face. Great attention was given to the fundamental subjects of this research in data collection and usage, and economic modeling to guide renewal decision making. The chapter leads into Chapter 3, which covers the development of the data standard introduced as part of the research objectives, as well as testing of legacy economic decision support tools, and further integrates practical evidence and research findings to support the need for fuzzy logic as evidenced in Chapter 4.

From the onset of modern drinking water systems, engineers have sought to develop standardized practices for effective pipe maintenance and replacement. These range from purely reactive approaches to empirical cohort survival curves, to comprehensive condition data collection efforts intended to support advanced AI-driven modeling. Modeling across the spectrums of strength and complexity still fails to adequately address the immense challenge current managers face: maintaining acceptable system reliability within constrained budgets. Complete model validation & adaptability, data quality, and collaboration are still not sufficient to allow such. Utilities lack adequate inventories and event records, whether in amount, quality, or both, and have not become adept at using models and tools in a consistently effective way.

The research sought to close these gaps by developing a national database of standardized cost data (from more than 30 drinking water nationwide and 200 inspection and renewal projects) aimed at the support and development of models and tools for water system management (WERF, 2013). Direct costs were gathered along with societal costs such as traffic burden and air pollution to provide a triple bottom line cost expenditure, and the cost trends analyzed to identify trends as well as best practices. The researchers then developed standards in data keeping and management to capture the true costs related to condition assessment and renewal engineering projects for drinking water pipelines. These standards were meant to enable drinking water utilities to analyze the cost data efficiently and define robust decision support. Further, it was meant to inspire confidence in drinking water utilities that collecting and reporting in this manner will enable robust cost trend and driver statistical analyses of an unmatched solidarity.

The following sections summarize the literature and practice review efforts and results, as well as conclusions and recommendations synthesized from the findings. These insights were critical to guiding the modeling efforts in a sound and effective way, as described in Chapters 3-4.

2.2. DATA COLLECTION PRACTICES AND CHALLENGES

Figure 2-1. Robust Data Handling to Support Effective Utility Management

The state of the research and practice review of the data collection efforts by utilities revealed that many if not most utilities fall short at collecting the quality and quantity of data needed for effective long term water main planning and management (EPA, 2002; ASCE, 2021). Critical information such as pipe vintage, soil aggressiveness and stray currents, crucial forensic information surrounding failures, and holistic inspection and renewal costs is missing, inaccurate, or not shared in a collaborative way amongst the stakeholders (Chung, 2009; Nezhad, 2020; ASCE, 2021). A lesser but persistent issue is that it is stored in inconsistent ways hindering robust analyses; this was true regarding cost data, the primary target of this research specifically (WERF, 2010; Halfawy, 2007). Inspection and renewal project financials were not being captured, stored, and postured for future use in the most effective manner; this limits industry practitioners' understanding of the true drivers of pipe performance (Beckwith, 2014; Sinha, 2004; Xu, 2019). The unfortunate result was that trend analysis, benchmarking, and more importantly consistent long-term O&M and capital planning driven by sound risk analyses supported by historical data were not being carried out, hence putting the users' health and safety as well as environment at risk, and failing to maximize use of public funds. This went beyond internal management systems where utilities failed to consistently agree on and track societal costs (traffic disruption, lost business revenues due to storefront obstructions, etc.) which are no less important to proper water system management.

In response to these findings, the researchers sought to design and pilot a standard cost data and storage collection methodology, as described later in the chapter. The novel framework included protocols for classifying Condition Assessment (CA) and Renewal Engineering (RE) intervention costs properly to support advanced analyses via benchmarking, trends, and decision-support modeling.

The key findings were as follows:

- Valuable data is often collected but not properly categorized, normalized, and vetted for advanced analyses required for best practices in utility management
- The inherent risk borne by each node could necessitate that data be captured along an effort gradient, thereby reflecting the risk of each node, more risk equals more and better data needed to adequately handle these more important section
- Collaboration amongst internal departments as well as other stakeholders (differing utilities in the same corridor space) is crucial to successful holistic infrastructure management
- Automated data extraction and storage in a GIS framework using standard fields and definitions can significantly reduce staff time and errors, and could drive the utility managers' modeling efforts to acceptable levels industry-wide

These revelations support the need for the universal cost data standard that greatly enhances understanding of the critical parameters driving physical and financial pipe failure, as well as set the foundation for planning based on sound modeling efforts. If utilities cannot produce these critical performance indicators, water systems cannot be managed in way that maintains public safety and the most efficient use of resources.

2.3. CONDITION ASSESSMENT

Many techniques exist in the industry meant to ascertain pipe condition without intrusion as summarized in Figure 2.2.

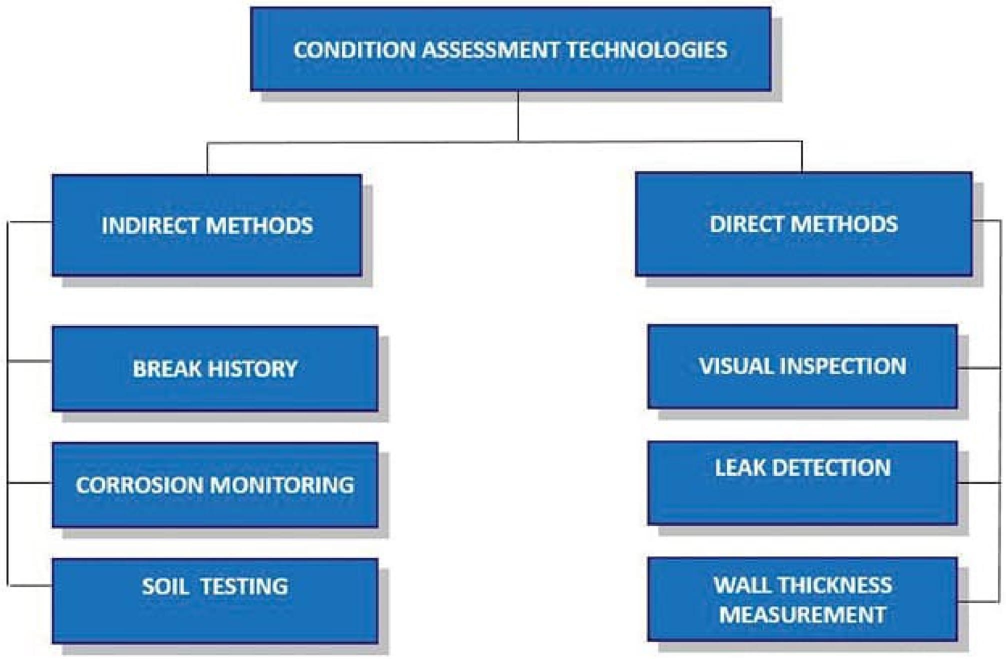

Figure 2-2. Condition Assessment Methods (Water Finance & Management, 2024)

Condition assessment tools range from simple microphones meant to listen for leaks at the valves, to advanced methods incorporating magnetic flux leakage or laser scanning. An example of advanced methods is found in Figure 2.3 which utilizes a remote field array technology able to assess condition in degrading pipes.

Figure 2-3. PICA Corp. See snake (Coghill et.al., 2018)

The literature and practice reviews of condition assessment tools and their apparent benefits and costs revealed many important findings. According to the USEPA (USEPA, 2012) most condition assessment (CA) work cannot be justified where the cost of failure is low, as is the case with most distribution mains. The study suggests the use of statistical-based, empirical failure models in place of active CA in smaller pipes for a more cost-effective approach. Also, the researchers concluded that when decision-support systems are coupled with CA work, a holistic-cost approach should be instituted in order to account for all other direct, indirect, and social costs in managing a pipeline. This would include scheduling all direct pipeline work so as to minimize these costs, as well as ensuring an optimal level of service for the customers as far as flow and quality expectations. The final message gleaned from the report was that while currently there is not a single practice to cost-effectively handle every circumstance faced by drinking water utilities, new technologies and tools are in development that will likely close these gaps and will ultimately drive the cost of CA down.

In the WERF Report entitled "Condition Assessment Strategies and Protocols for Water and Wastewater Utility Assets" (Marlow, et al., 2007), several points are made that were found to be seminal to this research.

First, the report was effective in defining all the costs inherent to CA work. These costs were grouped into direct and variable cost categories:

1. Direct
    a. Procedure/IT Development
    b. Data Management Systems/Software
    c. Implementation
2. Variable
    a. Inspection Frequency
    b. Inspection Quantity
    c. Access
    d. Training
    e. Reporting
    f. Analysis and Interpretation
    g. Tool Maintenance
    h. Costs from Incorrect Assessment

Surprisingly, the research determined that there was no concrete financial justification (outside of an explicit requirement or due diligence) for improved asset management programs containing CA initiatives, and was therefore driven by affordability rather than a cost-benefit analysis. The report states that the benefits of CA work for utilities are more assumed than evidenced by hard data. It further directs utilities considering CA programs to perform three integral steps prior to beginning the work. First, to estimate all benefits, both direct and indirect, of their intended CA program, including the "do nothing" option. Second, to estimate and compare all costs associated with each technology being considered, and last, to attempt to calculate the net financial gain associated with each option. Further, while the report admits that the benefits as a whole are difficult to capture, guidance is given via several methods in quantifying the gains. These methods include estimating the improved efficiency of O&M, the benefits of averting complete pipe failure, and the overall efficiency gains in the asset management program. Finally, guidance is given in cost-effective practices for CA. The report states that using high-level assessment tools initially can save cost in identifying areas with a higher risk cost. In addition, it states that no further assessment actions should be taken unless the benefits can be readily identified, which may not be entirely possible without some trial and error.

A third report from the USEPA gave some telling cost information on different technologies that were field-tested and evaluated (Royer, 2012). The project involved the demonstration of 12 different CA methods on a 76-year-old section of 24-inch cast iron pipe for 2,500 LF. Three technologies were tested for each category as follows: to find leaks, estimate wall thickness, provide external inspection, and perform an in-line inspection. The goal, as defined by the report, was to identify the performance of these methodologies in as near a real-world setting as could be established, in order to enable the various industry players to make better decisions as to their use. The different technologies used and their respective costs are shown in Table A1 (see Appendix A).

The conclusions made in the study relevant to this report include the following:

- Each technology operated and produced or reported data
- The demonstrated technologies, as tested or with improvements, can fill inspection niches
- Inspection cost ranged from \$3–\$19/lineal foot (LF) in addition to support costs at \$0.48–\$1.63/LF for the 10,000-LF pilot project

Similar research provided some useful information regarding the varying costs of CA with respect to the condition of the pipe itself, as well as the costs of failure (Misiunas, 2005). The research asserts that the costs of pipe failure management can vary greatly depending not only on the methods used, but also depending on the stage of deterioration in which the pipe is. The author asserts that the cost of the inspection usually decreases as the pipe condition worsens. Figure 2-4 shows the relationship between the costs in question as presented in the paper.

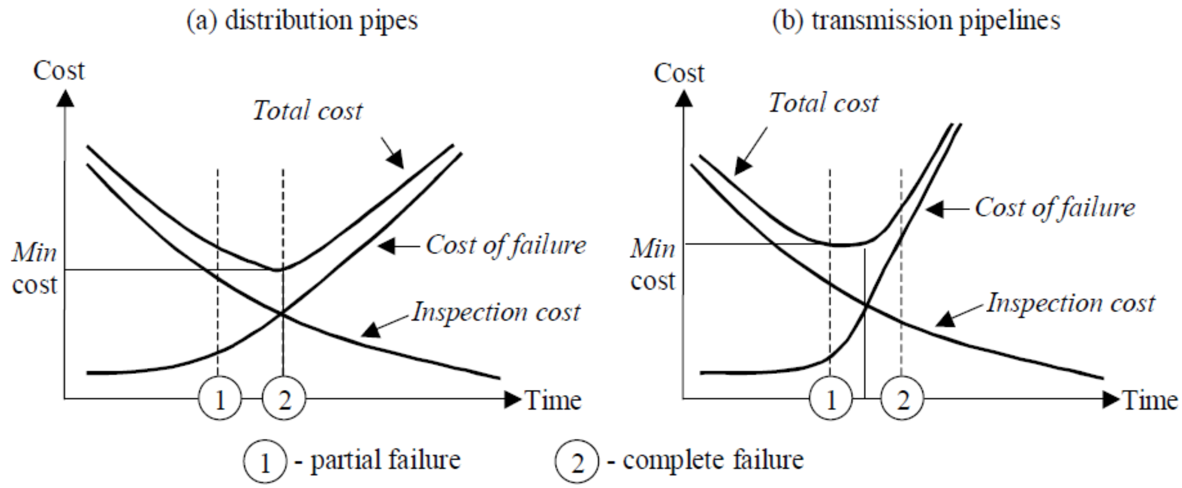

Figure 2-4. – Condition Assessment and Failure Costs over Time (Misiunas, 2005)

Further dialogue in the paper states that normally water utilities cannot afford the complex and intensive inspection techniques required in the early life stages of the pipeline, therefore lesser means are employed with lower standards of performance. The author suggests that the most economical choice is then where the cost of CA and failure meet. The paper continues that when the pipe is intact, the only real cost is the risk involved, whereas once the pipe has failed, the impact on the surrounding infrastructure becomes great. This is also due to the interruption or outage of water service to society.

A case study looked at Seattle Public Utilities' contract with Hydroscope, Inc. in the CA of some of their 8-inch cast iron water pipelines. The pipes included three separate sections: two installed in the 1920s and the other in the 1950s. The work also included a rehabilitation plan and financial analysis that would save the utility an estimated 68% over the cost of a traditional open-cut replacement, with a guarantee of an additional 15 years of service life. Wall condition descriptions were defined for consistent inspection results. The signal from the hydroscope was rated in order to give a confidence rating to the inspection results. This rating was termed the Signal Quality Index. A Hydroscope Reliability Analysis (HYREL©) model was performed to produce a cost-effective alternative to full replacement. All recommendations were prescribed for completion within one to five years, and estimated costs for performing each restoration measure were provided. Each cost estimate was believed to be sufficient to include the costs of any warranted reconnection and/or relocation of services. Notes on specifications for restoration measures were also given. The results of the work are shown in Table , where it's shown that the cost of the preemptive work is around one-third of that of traditional replacement under normal working conditions. Emergency replacement could further increase the cost of the work.

A case study on cleaning and cement mortar lining for unlined cast iron pipes belonging to Seattle Public Utilities (SPU) was completed in the WATERiD project. The project was undertaken by SPU as a pilot project, being their first one with this type of pipe rehabilitation. The pipe involved in the study included 8-, 10-, and 24-inch diameter sections for a total of approximately 19,000 LF plagued by tuberculation and hence experiencing capacity and quality issues. SPU included full-width pavement restoration, new valves, hydrants, fittings, etc., storm inlet replacement, new ADA ramps, temporary hydrants and flushing points with the work. In total, the project cost was twice the national average typical for this type of work, but it was still deemed only one-third of the cost of the average cost for a traditional open cut replacement. The lessons learned by SPU in the process began with the acknowledgement that this type of work typically falls within the range of \$32–\$65/ LF. Second, they concluded that rehabilitation of at least 30,000 LF of pipes should be attempted in order to fully absorb the other direct costs outside of installation, and the work would be best conducted as part of a long-term program to attract more contractors and eliminate excess mobilization costs. SPU also learned that data gathering for the work was more cost efficient when performed and stored after the work, rather than performing extensive, detailed analysis outside the scope of the immediate work. Lastly, they discovered that the loss of water revenues must be considered in the total cost of the work, since the temporary water services bypassed the utility's meters.

All CA data were compiled as a whole, regardless of type or pipe size, to give a broad idea of the current status of the industry. Figure A1 in Appendix A shows the unit cost by region. The data was sparse and often expressed in very different ways. Utilities typically sign a yearly contract for the services and therefore a unit cost per foot becomes difficult to capture and express according to date or project length. In lieu of this, interviews were performed with various utilities and internal documents gathered to gain the desired information on technology cost and how utilities were justifying their respective CA programs.

The Sewerage and Water Board of New Orleans (SWBNO) provided a great deal of assistance in this instance. The SWBNO's situation is unique in that their program is driven by the extensive damage caused to their pipelines by the flooding from Hurricane Katrina in 2005. SWBNO received funds from Federal Emergency Management Agency (FEMA) to remedy the problems and as a result, developed an assessment protocol for their water system to better capture and report the extent of the damage and what was being done to renew it to its previous state. The protocol would involve the testing and evaluation of the entire water system, provide recommendations for repair work, and establish certification criteria for measuring whether performance had been fully restored. The protocol was taken from AwwaRF and was as follows:

1. Review of Historical Performance Data
2. Water System Performance Goals
3. Water System Assessment
4. Issuance of Work Order
5. Update of Hydraulic Model
6. Reevaluation of Water System Assessment
7. Certification of Water System

The water system took on extensive damage from the flooding, including structural pipeline damage from the weight of the water, loss of pressure, trees being uprooted, saturated soil, and the entry of contaminated water. Leaks were caused throughout the system from the sharp pressure losses as well as the pipe displacement caused by the flood water. As the system came back online, population served dropped yet water supply increased, signaling a great deal of water loss through leakage.

As of late 2010, FEMA had provided nearly \$51 million in water point repair and associated paving to private contractors, nearly \$29 million to SWBNO for internal repair work, \$1.3 million in leak detection activities, and roughly \$7 million of for appurtenance repair for a total expenditure of \$88 million. As part of their extensive leak detection work, the utility performed a comparison of tools as a justification for the program, specifically SmartBall and Echologics LeakFinder®. Their analysis revealed the following results:

1. SmartBall can only be applied to lines larger than 10-inch in diameter and therefore could only be used on 26% of the system, or 416 total miles
2. SmartBall performed exceptionally well in certain circumstances: In locations where the risk of failure cost far outweighs the cost of the CA work
    a. When mains continue for a significant distance without lateral lines or other fittings prohibitive of the work
    b. If the line ends in a reservoir in case the ball is missed at the extraction point
    c. SmartBall and similar tools require a great deal of planning and support in preparation for and coordination of the work
3. The Echologics tool could be used on all sizes in their system and could hence be used on the majority of the system, and did not face insertion/extraction issues like the SmartBall
4. The Echologics tool required sensors to be placed at intervals of a few hundred feet, otherwise did not cause any of the cost increases associated with the intrusive nature of SmartBall™ as listed.

Costs of performing portions of the work were included in the documentation gathered. The total cost for the SmartBall was $280,700 for 14.27 miles of main surveyed of 43- to 50-inch diameter, wherein 46 leaks were detected. The contract was for $186,000 and the internal support costs were $94,700. This equated to $6,102 per leak found, or $3.73 per LF. The Echologics tool surveyed 71.51 miles of from 4- to 24-inches in diameter and successfully located 610 leaks. The total cost of the work was $1,104,650 which equates to $1,811 per leak or $2.93 per LF. SWBNO concluded that the Echologics tool was a better fit for this portion of their drinking water system due to the lower cost per foot and per leak, as well as the non-intrusive nature of the work. In all, it was determined that SWBNO has a long history of using acoustic leak detection services contractors to survey its infrastructure and provide responsive leak detection. The survey results were used to create work orders to repair pipes in the same way that other leaks were repaired. The leaks were not always been tracked separately from leaks discovered by other means, so historical data relative to leak detection response activities is limited. Additionally, activity involving the existing work orders was not specifically tracked. Recent CA activities have been focused towards providing data for the analysis portion of the FEMA-funded water line replacement program. The data is then used to consolidate or sequence multiple projects under multiple programs to minimize duplication of effort and inconvenience to residents and businesses. With a great deal of work being done under a variety of programs, it becomes very challenging to assemble unit cost data. In a similar application, AWWU recently had Pure Technologies perform SmartBall CA on 120,000 LF of transmission water mains. The target pipeline length originally selected was 63,000 LF, though this was increased to 120,000 feet to minimize the number of modifications necessary to create insertion and extraction points, and for ease of access at existing vaults and facilities. The SmartBall acoustical work was packaged with other CA work including of Broadband Electromagnetics (BEM) and corrosion analysis at selected excavation locations. The CA and consulting engineering work contract totaled $1.3 million.

The Washington Suburban Sanitary Commission (WSSC) conducts a comprehensive CA program for their large diameter PCCP pipes. This plan operates on a 6-year rotation and includes the inspection of all the 48” and larger pipes, for a total of 77 miles. This will be completed by the end of fiscal year (FY) 2013, whereas the beginning of FY 2013 will see the start of the inspection of an additional 68 miles of 36- and 42-inch lines through robotic means. Further, the six-year inspection rotation begins again in FY 2014 with coordination amongst departments to ensure that resources are available to support the intended plan. This work will involve SmartBall leak detection wherein the leaks identified will be followed up by manned inspections to verify and eliminate them as quickly and aggressively as possible. The manned teams will enter the dewatered pipes and employ visual, sounding, and sonic inspections to identify all trouble spots in the pipe. An additional measure is taken in the way of electromagnetic field testing to further determine how many wires in the pipes are broken and the current yield strength of the pipe. If a pipe is found to be near failure it is replaced and fiber optic acoustic monitoring cables along with data acquisition computers are installed in the pipe to “listen” for further wire breaks after it is placed back into service.

WSSC’s inspection costs averaged $150,000 per mile to inspect its PCCP lines, or a little over $28/LF. The inspections showed that only 1%–2% of these pipes needed rehabilitation. WSSC has replaced 32 feet of pipe per mile on average, while performing three repairs per mile using carbon fiber patching methods. The costs associated with the replacement and repair work are $80,000 and $70,000, respectively, per pipe joint (16 feet), or $5,000 and $4,375 per foot. The smaller diameters in the study will be mainly inspected through robotic methods in the future. This requires less service disruption as the pressure need only be reduced in the pipe rather than taken out of service, as does not require pipe entry by the workers. High-definition cameras will record visual data while electromagnetic testing will be done to determine wire breaks. The total cost of the robotic inspections is $80,000 per mile. Sounding and sonic methods will no longer be used, and this type of monitoring will now be performed using the fiber optic system. The current plan is to have all PCCP pipelines of 48” and larger fitted with this system by the end of FY 2013. In recent years, the system has proven itself a viable tool in mitigating catastrophic failures. The most marked event occurred near the end of June in 2010.

At this time, the system warned WSSC staff that wire breaks were occurring in a 96-inch PCCP pipeline, and they decided to take it out of service immediately. Upon excavation it was determined that a specific section of pipe was indeed near failure. The total cost of the replacement was $500,000, which was considered a financial win for the utility when compared to a failure in late December of 2008 of a 66-inch PCCP pipe. The direct costs of that failure alone were $1.7 million, while indirect costs were substantial as an enormous amount of water was lost and people nearby were placed in danger. The cost of the system is roughly $128,000 per mile, and annual monitoring costs are around $13,000 per mile.

WSSC currently feels that the system in place is effective since in practice less than 2% of all pipes need actual repair or replacement. The alternative is a comprehensive pipe replacement initiative, wherein WSSC feels that 98% of all pipes replaced still have useful remaining life. The entire system of PCCP pipes has been valued at $2 billion; hence $1.96 billion worth of pipe would be wasted.

2.4. RENEWAL ENGINEERING

USEPA states that "System Renewal includes a wide range of Repair, Rehabilitation, and Replacement techniques that bring the pipeline system to acceptable levels of performance within budgets" (USEPA, 2012). The decision-making process for the proper balance of repair, rehabilitation, and replacement is a function of the condition of the pipe, the lifecycle cost of the various RE (repair/rehabilitation/ replacement) options, and the related risk reductions. Renewal of pipeline systems are a unique challenge when compared with infrastructure assets like bridges, dams, and buildings, because they are "out-of-sight" and "out-of-mind." Common issues that are addressed through renewal efforts include corrosion, joint dislocation, tuberculation, and ground settlement. Numerous materials, installation methods, diameters, and construction practices are also in use, creating a challenge for the utility and the designer in selecting the most appropriate one. Comprehensive system renewal is further complicated by variations in physical, chemical, geographical, technical, and condition of existing and renewed pipe. The determination of the cost of various technologies for renewal of these assets is complex, and further research is needed into the various methods. Several common renewal methods were chosen for analysis based on their prevalence in the industry hence ease of access to available, quality data. These methods are defined in the following sections.

2.4.1. Cured-in-Place Pipe Liners

Cured-in-place pipe (CIPP) liners are used to seal and/or structurally renew existing pipes without excavation of the pipe itself. The basic CIPP liner is a tube, impregnated with a liquid thermoset resin, inserted into a pipeline and cured. The major classes of CIPP liners are described in terms of tube construction, insertion method, the resins used, and the cure method. The tubes can be manufactured from felt or fiber-reinforced materials, and are woven, unwoven, or spirally wrapped. CIPP is frequently used in highly urbanized settings where open trench work is highly disruptive and costly (EPA 2012; WERF 2010).

2.4.2. Pipe Bursting

With pipe bursting (for brittle materials) and pipe splitting (for ductile materials), the old pipe is ruptured and pushed into the surrounding soil, while a new pipe follows the cone-ended bursting tool to replace the old pipe. A key advantage of pipe bursting is that it allows for the upsizing of the original pipe. Depth, soil conditions, peripheral utilities, and service connections will dictate whether pipe bursting is appropriate (FHWA, 1995). It was found that the costs of failure increase much more quickly in transmission than in distribution, and the author attributes this to the size of the pipes involved. The author concludes by stating that the best practices involve the reduction of reaction time to failures, and further to integrate a proactive failure management plan into their workings. One WATERiD case study covered the inspections of a 66-inch diameter pipeline constructed in the 1960s by Aurora Water in Colorado. The pipe consisted of both a lined welded steel pipe and prestressed concrete pipe. The inspections were traditional in nature, including open excavation and visual inspections, as well as thickness measurement and sounding with a hammer. The research findings showcased the consideration of several lining alternatives for the utility, wherein

Table was developed to compare the costs and respective service lives. Polyurea was eventually chosen as the best alternative for the majority of the particular remediation needed, while epoxy was chosen in sections where spot repairs were specified.

2.4.3. Horizontal Directional Drilling

Horizontal directional drilling (HDD) is a “trenchless” method built for extenuating circumstances for installation and maintenance, whether under a water body, a major highway, or a structure, wherein HDD can provide an excellent alternative to an open cut excavation. The amount of readily available HDD data made it a good choice for this study.

2.4.4. Open Cut Replacement

Open cut replacement consists of the traditional method of pipe installation, where an excavation crew typically performs surface removal first. The surface is then leveled, if necessary, and a trench dug using a track excavator or backhoe. The existing pipe can either be removed through direct excavation or abandoned in place. Open cut work is typically very disruptive to the adjacent area and requires a great deal of traffic control, is typically slower than trenchless methods, and is also more dangerous as both workers and residents risk cave-ins when in or near the trenches.

2.4.5. CIPP

The CIPP work cost for water mains was first plotted by unit cost according to the pipeline diameter in Figure A2, which shows the unit cost per lineal foot (LF) for the various CIPP projects surveyed. The projects ranged from 6–14 inches in diameter, as shown, with the majority of the projects being 6 inches in size. The projects surveyed cost at a minimum of just under \$100/LF, and at a maximum of just over \$300/LF. A trend line was fit to the data of $y = 9.8231x + 76.503$ with an $R^2 = 0.1763$. Following the study of the costs as driven by pipeline diameter, the costs were then plotted to see how project length affected the unit cost per foot (see Figure A3); this projection shows how the project length of CIPP work is affected by the length of the work performed for a particular application. The data seem to converge on an average cost around \$125/LF after the length of the project reaches 1,200 LF. This is somewhat intuitive, though more data are necessary to begin to see any significant trends and/or potential cost drivers.

Lastly, the various supplemental direct and societal costs were broken out and plotted to see how they were driving the total project cost. Apparently, the only major contributors to the overall cost burden to society was the cost of traffic disruption, while the major components of project cost to the utilities were mobilization, testing and inspection, valves and fittings, and service reconnections. The various costs supplemental to CIPP work are shown by percentage of the total work, which shows that only five types of costs are adding to the cost of the projects in a significant way. Mobilization played the biggest role in the various supplemental costs beyond CIPP work, followed by testing and inspection, valves and fittings, and service reconnections. Safety measures were next in line in their influence on the overall project cost and consisted of items such as protective gear for workers entering manholes and trench protection. The provision of a temporary water main was the only other cost that is adding a noticeable amount to the total costs of the projects. The societal costs, however, are surprising in their overall effect.

The excessive traffic costs were due to the project in New York City. The low environmental noise costs were caused by a few of the projects taking place: Joint Base Elmendorf-Richardson (JBER) and a U.S. Air Force base in Alaska. These costs are not shouldered by the utility or municipality directly, but by society as a whole. The largest of these, traffic disruption, would be the cost to society of the hindered lane of travel in roadways considered important to commerce. As will be seen in other technologies for pipeline renewal, this is rather low, showing that the trenchless nature of this work provides a large advantage in relieving the burden on society. The level of business disruption is often correlated with the level of influence of traffic disruption, quickly growing as the project site nears the city centers. Yet, again, CIPP work creates a far better alternative for local business than methods requiring trenching and removal of the majority of the street and even walkways. Finally, the noise pollution related to CIPP work is shown as negligible; this is due to the nature of the work and the lack of extensive earth-moving equipment inherent to other methods of pipeline construction. Figure A4 shows the differing costs as a percent of the total cost burden. In this graph and those like it throughout the paper, the direct costs paid by the utility are shown by the darker bars, with the lighter bars representing the burden on society.

2.4.6. HDD

Next, HDD projects were analyzed, first to see how the unit cost was affected by the pipeline diameter. The data more or less follow a linear trend as costs rise with the diameter of the pipeline in question. Projects that were more costly than others of a similar size were those involving river crossings, using a heavier-rated pipe than others, or had access issues that drove the cost higher. Contractors that were afforded plenty of work space and the ability to access the area of the bore were able to bid lower prices. When the project unit costs for HDD work were plotted as a function of pipeline diameter, it was apparent that the costs mostly followed a linear trend. Some projects costs were due more to the heavier nature of the pipe or the limited access or room for mistakes, as in river crossings. Beyond that, the projects were all of a similar nature and strong trends for cost drivers were not apparent from the project context. The data were then plotted to see cost as a function of project length in Figure A5. This figure shows the unit costs for HDD work as affected by the length of the work completed in the specific project. A trend line was fit to the data of $y = 143.57x-0.218$ with an $R^2 = 0.1084$. The data mostly followed a power trend line, except for the project involving a river crossing and another using heavy-duty pipe. The data all fell under 4000 lineal feet in project length. Again, projects costing more had access issues or were driven as a function of the pressure class of the pipeline installed. Also, it appeared that as the project length surpassed 1000 LF, most of the projects fell within a lower unit cost range.

Finally, the other direct and indirect costs were plotted as a percentage of the total cost of the project in Figure A6, which shows that surface restoration and service reconnection accounted for the largest direct costs associated with the work. This was caused by work in city streets, where extensive excavation work was performed in order to accommodate the drilling pits and warranted extensive restoration efforts. Valve and fitting installation also accounted for large portions of the project costs. Traffic disruption and lost business revenues accounted for a substantial amount of burden to the community, while noise pollution was of a lesser nature at ~2% of the total cost.

2.4.7. Open Cut

Then, the cost data for open cut replacement was plotted. A trend line was fit to the data to show where the average cost was falling. Most of the smaller diameter projects were seeing costs in the \$20–\$100/LF range. The projects that appeared inordinately high were very short in length. The trend line was $y = 4.3885x + 22.482$ where $R^2 = 0.1813$. Projects that exceeded this mark were mostly of a shorter length and required immediate attention rather than being a part of a large routine project. It appeared that as utilities were thinking ahead and rehabilitating old lines rather than fixing them after they had become a problem were seeing a great deal of cost savings per LF. The unit cost by pipeline diameter can be seen in Figure A7, which shows the data for the open cut projects surveyed. The unit cost data were then plotted for open cut work by the length of the project, as shown in Figure A8.

The percentage of total project cost that various supplemental direct and societal costs comprised was then plotted, which shows the average of the contribution to the total cost of the work from each type of cost related to open cut work. The lower bars in Figure A9 represent the other direct costs of the work such as mobilization and service reconnections. Valves and fittings, user services, and surface restoration played major roles in supplemental costs and were actually lower in this case than trenchless methods as the ground was already open from the pipeline installation. The societal costs are worth noting as they create a much, much larger burden on society than their trenchless counterparts. This is intuitive as it is commonly known that open cut work is far more obstructive to society with lane blockage, with entire road closings being the norm rather than the exception. Also, heavy excavators, dozers, frontend loaders, and so on create a great deal more noise than pipe lining, drilling, and bursting projects.

2.4.8. Pipe Bursting

Pipe bursting in drinking water pipe renewal was first plotted by unit cost according to pipeline diameter in order to determine trends and drivers to show the unit cost of pipe bursting per LF and how it may change according to the inner diameter of the pipeline being renewed. Data were gathered in the range of 4 to 12 inches. Data were much more easily found in the 6- and 8-inch sizes. Projects with more excessive costs were shorter and had limited access for entry and exit holes. Though a great deal of data is not available in this category, it is apparent that the majority of smaller-diameter projects would fall in the \$30–\$150/LF range. As the diameter increases, it appears likely that this trend will not continue. This is shown in Figure A10. Lastly, the other direct and indirect costs were graphed by percent of the total item cost, as shown in Figure A11.

The results of the cost breakdown were interesting in that the valves and fittings were so much of an influence on the total cost. This shows that pipe bursting a project in long runs without any branches or services can be very cost effective, yet, for every fitting, service, etc., that needs to be installed, this can heavily influence the overall cost of the work. Of the direct costs related to the work, valves and fittings accounted for the largest percentage of the cost. Service reconnections played the next biggest role in the various supplemental costs in addition to the pipe bursting work, followed by surface restoration, main reconnections, and old pipeline abandonment. Earthwork was next in line in its influence on the overall project cost and consisted of items such as test pits and the like. Mobilization (which frequently includes bonds and insurance, but is also often limited as a percentage of the total contract, for example, no more than 3%) did not significantly drive the cost in most cases, though they were often significant amounts of money. Utilities were able to take advantage of economies of scale and to absorb much of these costs into a great deal of rehabilitation work. The remaining categories of direct cost can be seen as not overly crucial in determining the overall cost of the project, each falling below 2.0% of the total cost. The societal costs were not significant in their overall effect. These costs are not shouldered by the utility or even the municipality directly, but to society as a whole. The largest of these, traffic disruption, added less than 5% of the total cost of the work to society.

2.5. DATA STANDARD

Data was received from several utilities participating in the WATERiD project, from over 30 utilities for a total of 190 cases in all. The data was collected into a database and then standardized. Graphs and tables are provided to show the story that the data is telling about the industry practice. All costs were converted to July 2012 dollars using RS Means 2013 and referenced from their respective areas to the average cost nationwide for heavy construction. Once the project characteristics and direct cost data were compiled, information was collected from the Internet concerning the average annual daily traffic (AADT), approximate number of surrounding businesses near a project that may have been affected by the work, and the average home price in the area (DOT records, Zillow, Google Maps).

These data were then used to estimate the societal costs of the project, as performed in previous research (Jung, 2007). A good-faith attempt was made to determine a best estimate the AADT on the roadways from the DOT sites on the Internet containing historical counts for the specific roadways. If an exact street was not named by the utility, average AADTs, home prices, and the number of surrounding businesses were determined from a brief survey of the area in Google Maps and various real estate websites (e.g., Zillow, Trulia, etc.). In cases where information differed, values were chosen on the more costly side. The final results were compiled, averaged, and expressed.

Equations developed from this study can be found in the work by Jung and Sinha (Jung, 2007). As an example, working days with traffic control for a typical open cut project might be 10 days, or 80 total hours using eight-hour workdays. If the project took place in a busy residential area, a typical AADT would be 3,000. The equations from the previous study would then become Equation 2.1 (Jung, 2007):

Equation 2.1:

Log10 (Cost) = 0.00022 x 3000 + 3.5556 or nearly $17,553

The analysis tool developed for the loss of revenue for local businesses was based on a study conducted in 2004, the formula for which is shown in Equation (2.2) (Gilchrist, 2005):

Equation 2.2:

LOP1 = (number of employees affected) × (average hourly output, $/h) ×

(productivity reduction factor) × (project duration; h)

Previous researchers (Jung, 2007) also developed a method for calculating the environmental cost of noise pollution caused by pipeline construction. From this, a noise depreciation index (NDI) was developed to estimate the possible depreciation of property values based on the aversion to the increase in noise. The researchers then applied an equation using the NDI and the increase in noise for a given project; that equation is shown here as Equation 2.3:

Equation 2.3:

0.0017 × K (additional dBAs of effective noise level) × original housing price = $ (Noise Cost)

The same researchers used an example of a 20-decibel increase brought about by an open cut excavation project to an area where the median home price was $118,900. The average noise cost for a year then becomes 0.0017 × 20 × 118,900 × 30 = $121,278. The article established the dBA increase for trenchless technologies such as pipe bursting as only 10, thereby only accounting for half the cost of traditional open cut projects.

2.6. RECOMMENDATIONS

This chapter summarized the development of a novel drinking water pipeline RE cost data and metadata collection and reporting methodology as part of the WATERiD project. The authors employed an ETL tool for collecting cost data from nearly 200 RE applications from over 30 drinking water utilities in the U.S. While this is a major advancement to current practices, the data is still lacking in order to be able to perform robust trend analyses. The cost data graphs shown in this paper were a result of piloting the methodology, which can only give a high-level view of current industry practices. Once industry professionals begin to adopt this process, it will drive best practices in infrastructure cost management to unsurpassed levels, and greatly benefit the global drinking water industry.

The RE techniques analyzed here included open cut replacement, cured-in-place pipe lining, horizontal directional drilling, and pipe bursting. Of the direct costs involved, it appeared that valves and fittings, service reconnections, and surface restoration accounted for the majority of the additional costs respective to the work. Of the indirect costs, traffic disruption appeared to be the greatest social cost to the consumer. It was also found that utilities do not collect all the useful cost information in pipeline management, and that a standardized data capture and reporting methodology would be of great value to industry. More importantly, it was shown that utilities were willing participants in this study, evidence that they saw great value in this type of work concerning the creation and implementation of a central cost data standard and database, by which data could be collected, analyzed and shared. Cost data management is an important aspect of any infrastructure management system. While the most commonly used level of data storage and management involves the use of a computerized database system not created specifically for capturing and leveraging condition assessment and RE cost data, greater sophistication in data management is required in order to more effectively create a basis upon which management decisions can be made with respect to initiating RE work for drinking water pipelines. Armed with standardized, quality data, utility managers can defend budget requests and more effectively manage their water pipeline infrastructure. Where the initial research effort formalized cost both data collection and use in advanced analyses and modeling, the next stage explored the veracity of finding success in water main optimal renewal strategy selection and timing.

2.7. MODELS AND TOOLS

2.7.1. Modeling Alternatives

Modeling alternatives for water main deterioration and renewal intervention prioritization covers the spectrum from basic linear regression to advanced sensor-aided real-time AI frameworks. Many comprehensive frameworks have been developed to guide renewal decisions. (Moglia, 1999, 2006, 2008). Early models provided important insights for modeling failure intervals, but lacked the ability to handle uncertainty and failed when model adaptability was crucial to maintaining projection accuracy. This section outlines the various types of models in current practice to guide municipal water system asset management and explores their strengths and weaknesses as well as utility in the day-to-day industry operations. An outline of the various models can be seen in Figure 2.5.

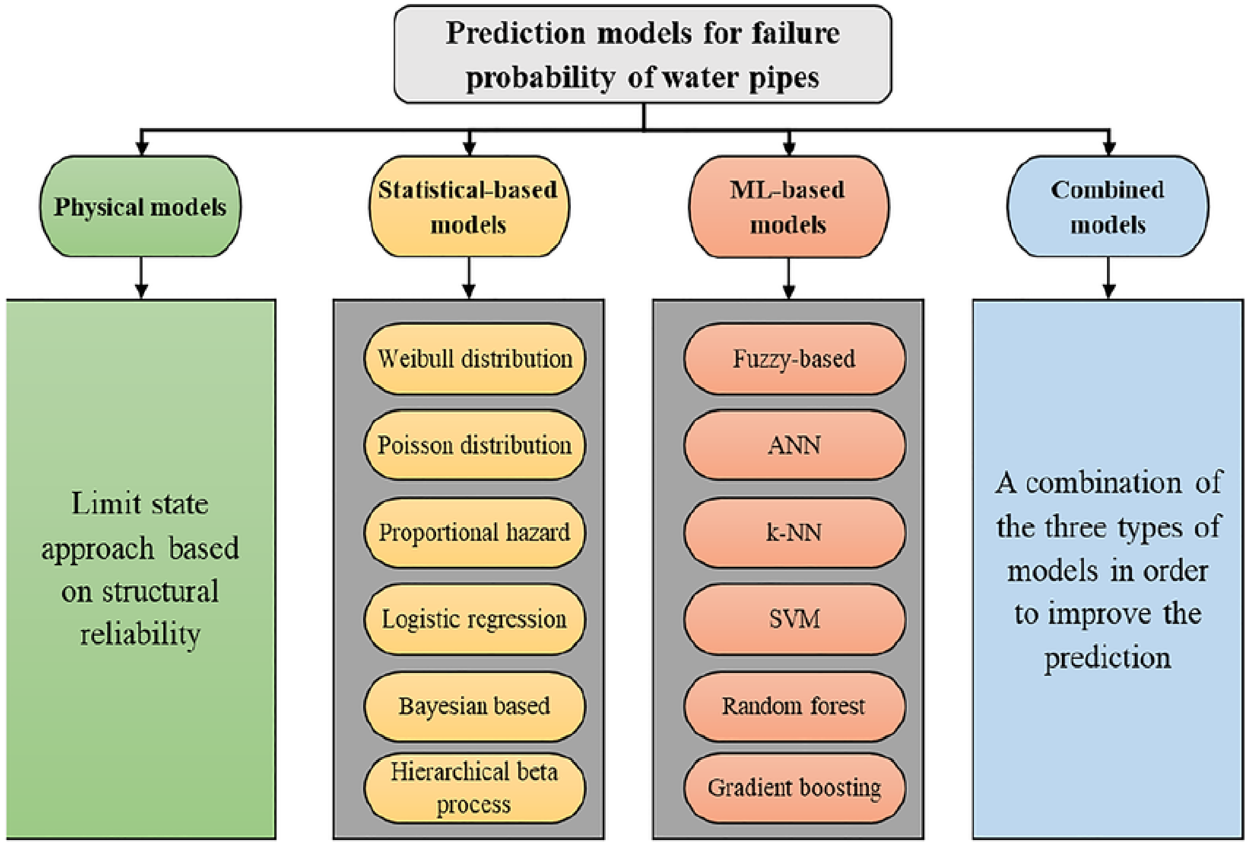

Figure 2-5. Models for Water System Asset Management (Taiwo et. al., 2023)

2.7.2. Deterministic Modeling

Early efforts to model pipe failure began with deterministic methods, applying lessons learned from patterns observed in the field to performance prediction. Primary examples include regression tools and survival curves using easily obtained data to estimate end of asset life. Although easily understood and implemented, they could not properly handle uncertainty or moreover the dynamic, complex nature of buried pipe behavioral performance. One such model relied on the relationship between the pipe wall and soil characteristics as well as the physics of failure, yet was constrained by its empirical roots and rudimentary assumptions (Rajani, 2000). Empirical results often limit successful modeling by these limitations, as can be seen in the line fitting to actual pipe failure in Figure 2.6.

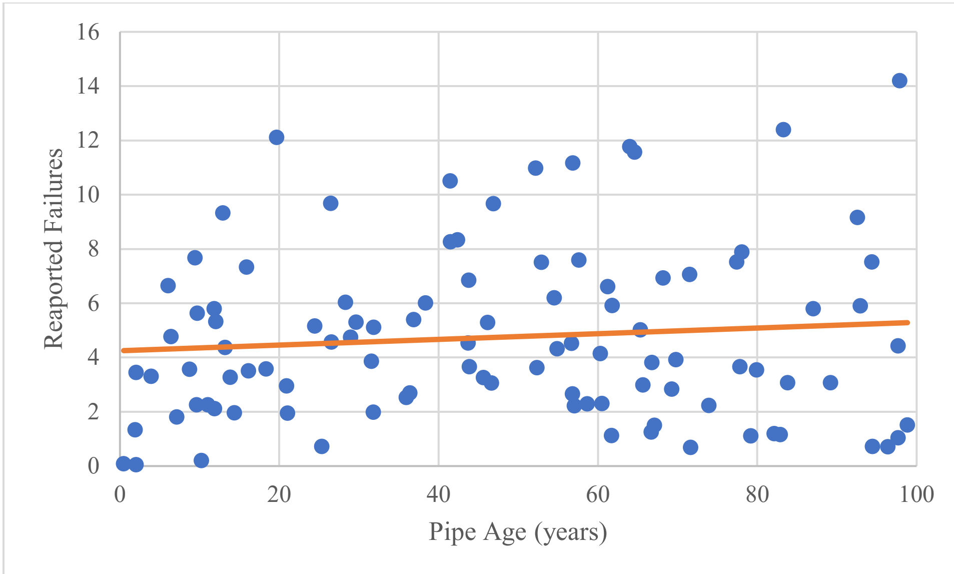

Figure 2-6. Empirical Regression Curve vs. Observed Pipeline Failures

These models were improved upon by introducing statistical methods such as frequency and cohort analysis, as in exponential regression, which predicts the likelihood of failures over a planning window. However, when data was missing or not well-normalized the models failed to properly account for the critical relationships amongst the true parameters driving the failures such as traffic vs. water table vs. pressure transients, for example.

2.7.3. Probabilistic and Economic Modeling

To ascend beyond the limitations of these early modeling efforts, probabilistic modeling was then explored which could better handle uncertainty in the key drivers such as age, soil, water table, and pressure transients, amongst others, varying enough within systems and moreover greatly across geographic regions. Unconstrained by reliance on distinct values, assuming a range of possible outcomes with accompanying probabilities for such provided more realistic answers to researchers and utility managers. Bayesian, Monte Carlo, and Weibull analyses, for example, have been widely researched and implemented with varying levels of success. One study sought to mitigate the effects of incomplete historical records by using censored data to compute survival curves, yet sample size and the quality of data greatly varied the results (Rajani, 20001). Furthermore, they failed to handle the interdependence of variables properly as well as disallow the hardcoding of expert heuristics. Figure 2.7 illustrates the differences in how basic deterministic models predict failure vs. more advanced probabilistic models, where the allowance of a range of results can better capture the actual pipe behavior.

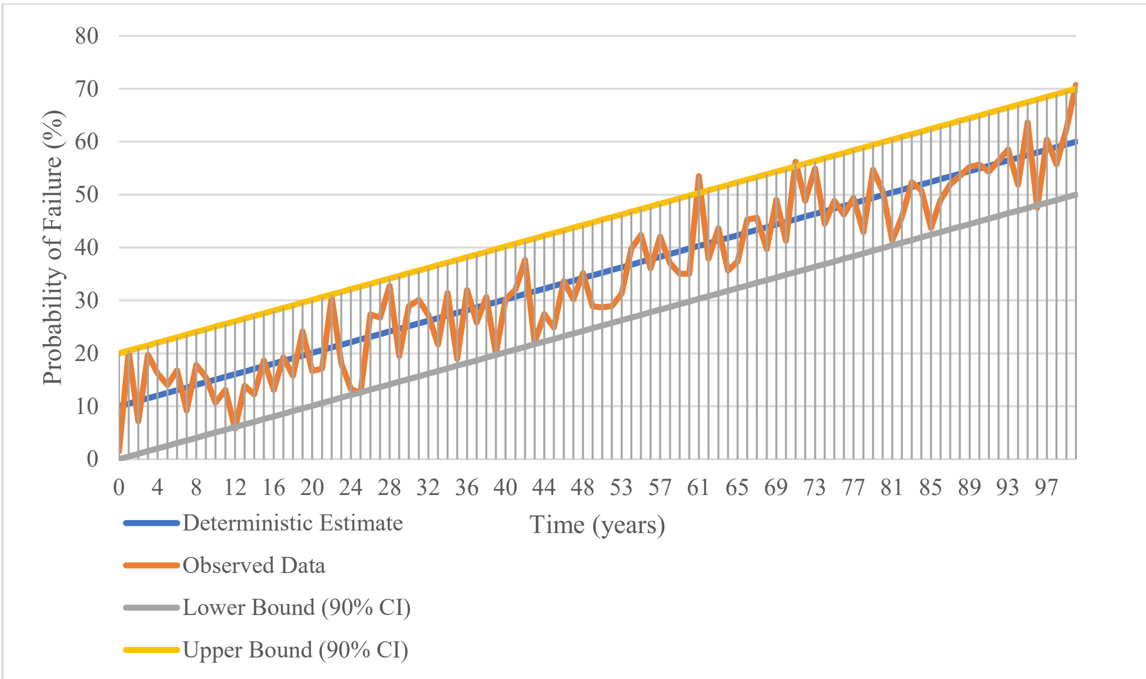

Figure 2-7. Deterministic vs. Probabilistic Failure Estimates

Economic models, such as those using marginal costs or life cycle costs were then explored to see how well an understanding of historical and predicted pipe financial performance could guide inspection and renewal intervention efforts to match industry best practices. When failure costs and drivers are well known and established for cohorts within a utility (likely based on vintage, and pipe corridor of little variations in soils and other significant differences) they can be of value at a high level. Any introduction of complexity such as uncertainty, or dynamic planning scenarios causes them to quickly lose their effectiveness as sound, primary decision-support tools.

2.7.4. Artificial Intelligence and Soft Computing

More recently water main renewal guidance has been substantially enhanced by soft computing techniques due to their excellent handling of the dynamic, uncertain and complex behavior of the mains. These methods include artificial neural networks, fuzzy logic, and adaptive neuro-fuzzy inference systems (ANFIS) that can be calibrated based on expert heuristics and historical data. Modeling techniques such as these work well where limited data is had regarding the current condition of the pipe and the environment in which it dwells, for example unknown soil aggressiveness and resistivity, water table fluctuations, and pressure transients. Fuzzy logic-based modeling was shown to have a higher accuracy at selecting proper renewal alternatives then previous models when it combined physical pipe performance parameters with environmental characteristics (Chen, 2012)(Mohammadi, 2008)(Vishwakarma, 2018). These models allow for several levels of input variability as typically static parameters such as soil aggressiveness is not restricted to a few hard values, rather can easily represent an entire range of values, and in Type 2 modeling are even allowed to span the boundaries enough to handle even more uncertainty yet. The effectiveness of this capability is showcased in Chapter 4.

Similarly, ANFIS outperformed regression models in failure prediction, yet, despite the success of these models, their adoption by utilities remains sparse due to inherent limitations stemming from the great deal of effort required in calibration and difficulty in using them to directly decide renewal priorities (Tavakoli, 2018). WERF and UKWIR performed benchmarking of tools such as KANEW and PARMS by comparing ease of use and historical success found that the earlier static models are more easily implemented, yet fail to work under uncertain conditions. Later models performed better when facing conditions modeled less easily, yet required advanced training along with time-consuming calibration to operate adequately. Artificially intelligent models were similarly tested and proved to be cumbersome to train as well as exhibit a black box like operation that eroded user credence; hybrid versions that combined empirical rules with heuristics proved to be more successful at providing utility and accuracy in decision support. Despite practitioner and researcher efforts, few tools have achieved marked success industrywide due to hurdles like data scarcity and quality, adequate tuning, and project selection accuracy.

While many methods have been developed and utilized, mixed success is still the story in the industry due to challenges collecting quality data and being able to adapt the models for ease and success of use. Table 2.1 summarizes the abilities and problems inherent in the model types referenced.

Table 2-1. Model Uses and Limitations

Model Type	Strengths	Limitations	Ideal Use
Deterministic (e.g., regression, survival curves)	Utility and transparency	Cannot handle uncertainty and variability in key parameters	High level screening
Probabilistic (e.g., Weibull, Markov)	Handles uncertainty	Less easy to understand and accept directives	Failure modeling amidst uncertainty
Economic Models (e.g., EUAC, LCCA)	Financially based	Deterministic nature limits abilities	Cost-benefit analysis
AI/ML-Based (e.g., neural nets, decision trees)	Highly adaptable, learns from data patterns	Must have very large datasets, black box-like	Pattern finding
Fuzzy Logic Models	Accounts for uncertainty and dynamics	Based on expert heuristics, time consuming to calibrate	Decision support at project level

These models were benchmarked as to their ability to adapt to complexity and uncertainty, their adoptability, and furthermore accuracy in choosing the best renewal intervention method and timing. Performance examples are shown in Figures 2.8-2.9 below where the various types of models are compared on their ability to manage risk over the planning window as well as to maximize net present value.

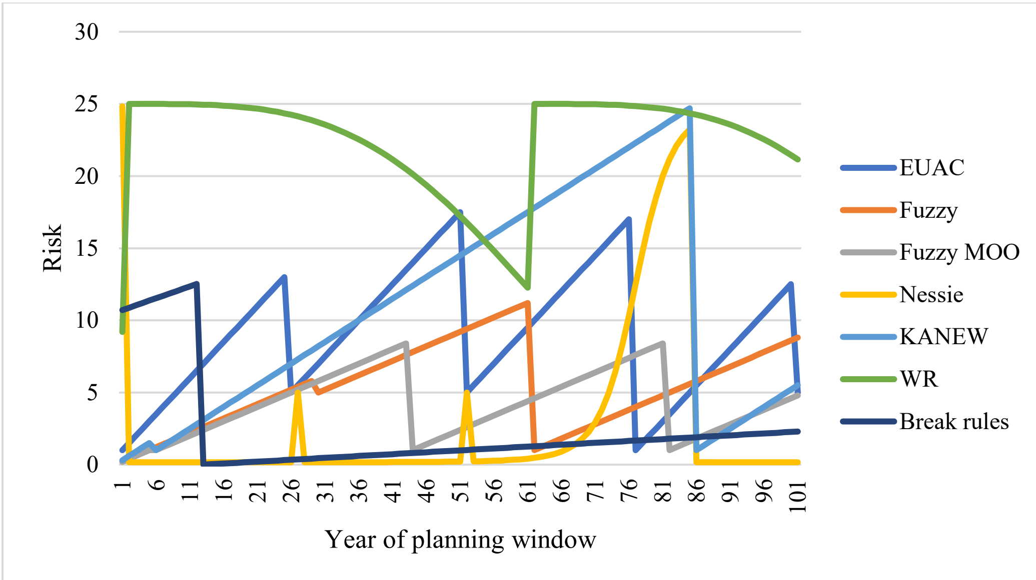

Figure 2-8 . Modeling comparison based on Risk

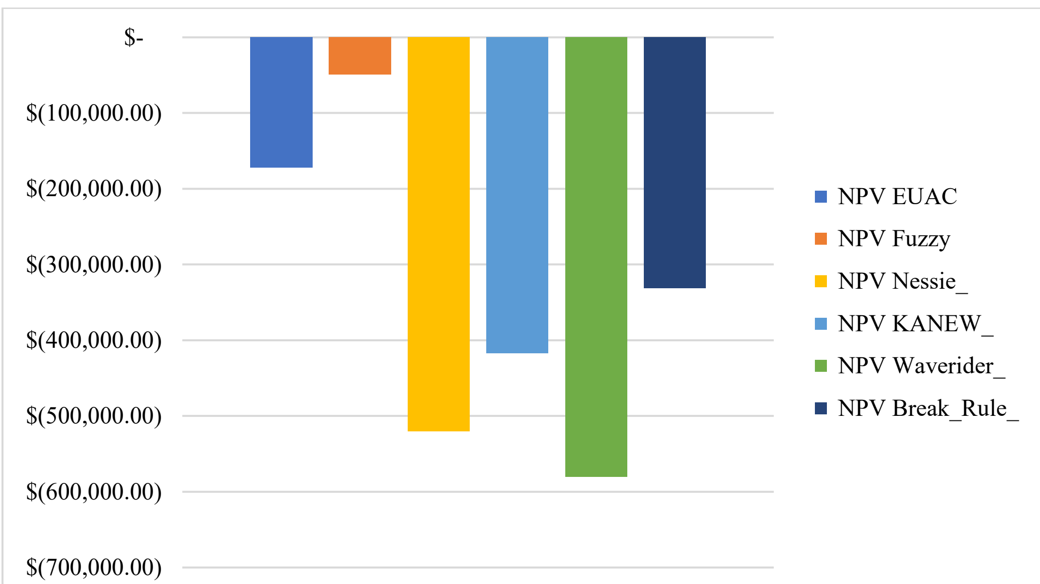

Figure 2-9. Model comparison based on Net Present Value (NPV)

2.7.5. GIS and Real-time Sensor Integration

Advanced utility asset management models require spatial understanding to effectively guide decision-making; hence GIS support has become integral in this manner. Coupling physical and financial performance trends for individual pipe nodes with choropleths of varying significant factors such as soils, pressure transients, and traffic provides powerful imagery that shows a holistic, smart view of the system's behavior and vulnerabilities (Figure 4.4). Integration with real-time data will come in the next generation of advancements but only provide more, better data to drive advanced AI-tools that require very large datasets, but currently their lack of widespread use and validation inhibit industry-wide adoption.

2.8. SUMMARY AND IMPLICATIONS

This chapter contained comprehensive reviews of the current state of affairs in the water utility asset management space, covering current condition assessment and renewal engineering practices and their respective costs, data collection and storage of key information about the pipes and systems, and finally the wide spectrum of modeling techniques and the inherent challenges practitioners face in using the available resources to manage the systems in the very best way. In each facet shortcomings still remain including missing or low-quality data, ever-increasing costs of providing clean drinking water at maximum reliability, missing staff training for and confidence in models and tools. These issues translate into inefficient use of budgets, substandard service, as well as potential harm to users and the environment. Chapter 3 delves into the research efforts that have sought to close the gap between the *current* state of the practice and *best* practice.

3. ENGINEERING ECONOMIC EVALUATION OF PIPELINE RENEWAL STRATEGIES

3.1. INTRODUCTION

Since the 1990s, life cycle cost (LCC) and equivalent uniform annual cost (EUAC) analyses have been foundational in infrastructure investment decision-making, driven in part by legislation such as the 1991 Intermodal Surface Transportation Efficiency Act (ISTEA). While these frameworks remain widely used, their limitations have become increasingly evident as aging water and wastewater systems face rising failure rates and service disruptions. Traditional LCC/EUAC models typically assume fixed service lives, linear degradation, and constant costs, assumptions that overlook spatial heterogeneity, stochastic failure mechanisms, and systemic interdependencies (Clark et al, 2002). These simplifications result in predictions that often underestimate true risks and economic impacts, making effective capital planning unnecessarily difficult.

This paper presents a unique integration of empirical infrastructure data with classical engineering economic principles to modernize pipeline renewal evaluation. Using the nationally comprehensive PIPEiD and WATERiD databases, developed through collaborations with over 500 utilities and federal agencies, this research offers the most empirically robust cost and performance data available for buried pipelines.

This research focused on developing the LCC/EUAC models from abstract financial tools to field-informed decision-making frameworks for choosing appropriate renewal strategies under real-world constraints. This work began new data collection protocols within WATERiD, informed the early development of PIPEiD's renewal modules, and revealed important shortcomings in earlier industry tools, such as the Water Environment Research Foundation's Life Cycle Cost Analysis (WERF LCCA), the Environmental Protection Agency's (EPA) Economic Analysis System Tool (EAST), and the Infrastructure Risk Assessment Model (IRAM). Despite their potential, these models often came up short due to oversimplifying assumptions, limited scalability, and mathematical instability.

This chapter serves a dual purpose. First, it delivers an empirically validated economic evaluation of four common renewal strategies: do nothing, inspect/maintain, repair (e.g., Cured-In-Place-Pipe (CIPP)), and replace, using a dataset spanning over 985,000 pipe segment records and 37,000 failure events. Second, it presents a constructive critique of deterministic cost modeling, laying the foundation for the uncertainty-aware, spatially responsive model introduced in Chapter 4. In doing so, it captures the academic direction and practical contributions of the author's early research, while signaling a paradigm shift toward more adaptive, data-driven asset management models.

3.2. METHODOLOGY

The research explores a practical, data-informed methodology that bridges classical engineering economics with real-world infrastructure performance. The primary objective was to evaluate and compare multiple pipeline renewal strategies using classical LCC and EUAC metrics, while accounting for spatial, material, and contextual variability through calibration with real-world datasets. It also details the design philosophy, analytical structure, and empirical foundations of the spreadsheet-based model.

3.2.1. Evaluation Framework

Four widely practiced pipeline renewal strategies were selected based on documented utility practices across the United States and frequently observed renewal scenarios recorded in the WATERiD database. These strategies were chosen because they represent the most common approaches used by utilities nationwide and are well-documented in the database:

- Do Nothing: No planned or proactive maintenance or repair; the pipeline is allowed to deteriorate naturally until failure, assumed at year 10, after which emergency repairs are initiated.
- Inspect and Maintain: Periodic condition assessments combined with preventive maintenance activities are designed to detect and address early signs of deterioration, extending the pipeline's service life by an estimated 20 years.
- Repair (e.g., CIPP Lining): Targeted trenchless rehabilitation methods that restore structural integrity and delay replacement, with an assumed post-repair service life of 30 years.
- Replace: Full pipe replacement, typically conducted via open-cut excavation or horizontal directional drilling, resetting the asset's service life to a 50-year lifespan.

This set of renewal strategies captures the conventional options available to most asset managers and aligns with hundreds of documented WATERiD renewal cases. A 50-year planning horizon was adopted, consistent with American Water Works Association (AWWA) M77 recommendations and standard municipal depreciation schedules. A baseline real discount rate of 5% was used, with sensitivity analysis conducted at 3%, 4%, 6%, and 7%, by EPA guidance for evaluating capital improvement investments. A 5% discount rate was used due to its common appearance in industry.

3.2.2. Cost Elements and Data Sources

The model breaks down each renewal strategy into standardized cost components to ensure consistency across evaluations. These components include:

- Initial Capital Cost: The upfront expense of construction or intervention at the start of the project.
- Annual Operations and Maintenance (O&M) Costs: Recurring costs for routine upkeep and minor repairs throughout the asset's service life.
- Inspection Costs: Scheduled expenses for periodic condition assessments during the asset's lifespan, distinct from regular maintenance.
- Disposal Costs: End-of-life costs including excavation, hauling, and any necessary environmental remediation.
- Residual Value: The estimated salvage or remaining economic value of the asset at the end of the planning period.

Input values were derived and cross-validated using three primary sources:

1. WATERiD Cost Benchmarking Tables: Data from 190 utility-submitted renewal case studies providing real-world cost ranges for maintenance and replacement strategies.

2. PIPEiD Performance Datasets: Empirical data used to estimate asset longevity and typical maintenance practices observed nationwide.

3. Industry Standards and Technical Literature: Including AWWA Manuals M28 and M77, as well as peer-reviewed studies in engineering economics and asset management.

This integrated approach produced a cost matrix that, while organized according to classical LCC principles, is grounded in observed asset behavior rather than theoretical assumptions.

3.2.3. Model Implementation and Transparency

The model was developed in Microsoft Excel using a fully transparent, macro-free structure to maximize accessibility, auditability, and user adaptability. In contrast to restricted-access tools that obscure key assumptions or restrict customization, this model enables users to modify any cost, rate, or time-based input and immediately observe the resulting changes in equation 3.1 LCC and equation 3.2 EUAC (Fuller, 1996) outputs. Users can readily explore how changes to inputs affect outputs, supporting both decision-making and educational applications.

The LCC and EUAC were calculated using the following formulas:

Equation 3.1:

$$LCC = C_0 + \sum_{t=1}^{N} \frac{C_{O\&M,t} + C_{I,t}}{(1+r)^t} + \frac{C_D - C_R}{(1+r)^N}$$

Equation 3.2:

$$EUAC = LCC \cdot \frac{r(1+r)^N}{(1+r)^N - 1}$$

Table 3-1. Variables Used in LCC and EUAC Calculations

LCC	Total Life Cycle Cost over the analysis period
$EUAC$	Equivalent Uniform Annual Cost
C_0	Initial capital cost
$C_{O\&M,t}$	Operations and maintenance cost in year t
$C_{I,t}$	Inspection cost in year t
C_D	Disposal cost at end-of-life
C_R	Residual value at the end of the analysis period
r	Real discount rate (e.g., 5%)
t	Year (from 1 to N)
N	Analysis period in years (e.g., 50 years)

These equations allow comparison of strategies with different capital intensities and service life durations on a common, annualized financial basis. To ensure the model accurately reflects real-world pipeline behavior, it was calibrated using extensive empirical data from national infrastructure datasets, bridging theoretical assumptions with observed performance.

3.2.4. Empirical Calibration and Probabilistic Extensions

To address the limitations of deterministic point estimates, the model was calibrated using empirical data distributions from PIPEiD and WATERiD. For example, survival curves for large-diameter ductile iron pipes in freeze-thaw environments exhibited nonlinear failure behavior, with a coefficient of determination (R^2 = 0.89), reinforcing a 30-year service life assumption for repairs (CIPP). Societal costs, such as traffic disruption and noise pollution, were also incorporated using published estimates, including a 10-day lane closure cost of $17,553 (Welling and Sinha, 2014).

To support more advanced sensitivity analysis, a Monte Carlo simulation module was integrated. This feature enables users to conduct 1,000 randomized trials across probability disruptions for key variables such as service life and cost inputs. The result is a more robust model for exploring uncertainty and scenario-based decision making in pipeline renewal planning.

With the calibrated model in place, the following section analyzes and compares the lifecycle costs and economic outcomes of each renewal strategy, highlighting the practical implications for utility asset management.

3.3. RESULTS AND FINDINGS

This section presents a comparison of LCC and EUAC outcomes for the four pipeline renewal strategies under consideration. The analysis is drawn from data in the PIPEiD and WATERiD platforms, offering a robust overview of diverse utility practices, environmental conditions, and observed deterioration patterns. The results are organized into three areas:

1. Baseline comparisons
2. Sensitivity to discount rate assumptions
3. Influence of spatial risk factors and societal cost considerations

The financial analyses were first run with a standard discount rate of 5% across various scenarios on data collected as part of the research. This section presents these baseline results and reviews how variations common to the industry impact the outcomes derived by the financial tools. In reality, financial drivers vary greatly across various utilities and even in different hydraulic zones/sections of the city. To evaluate how these variations affect decision making, different combinations of the key drivers, from most conservative to most risky were modeled and outcomes observed by comparing the recommended renewal strategy to best practices as guided by AWWA M28.

Table 3.2 summarizes the input parameters, which are derived from the WATERiD cost benchmarking database and adjusted using empirically validated service life distributions from PIPEiD. Notably, replacement strategies show the highest initial costs but lower annual operating expenses, highlighting the trade-offs between upfront investment and ongoing maintenance.

Table 3-2. Standardized Input Parameters for Pipeline Renewal Strategies

Strategy	Initial Cost ($)	O&M ($/yr)	Inspection ($/yr)	Service Life (yrs)	Residual Value ($)	Disposal Cost ($)
Do Nothing	0	1,000	0	10	0	5,000
Inspect/Maintain	5,000	800	300	20	1,000	2,000
Repair (CIPP)	10,000	400	0	30	2,000	1,000
Replace	25,000	100	0	50	5,000	2,000

Figure 3.1 shows the sensitivity of the EUAC model to industry ranges. Of note, the average error increased from 0.68 (best-case) to 1.30 (poorly-delivered), proving the need of extensive calibration and the unreliability of deterministic predictions.

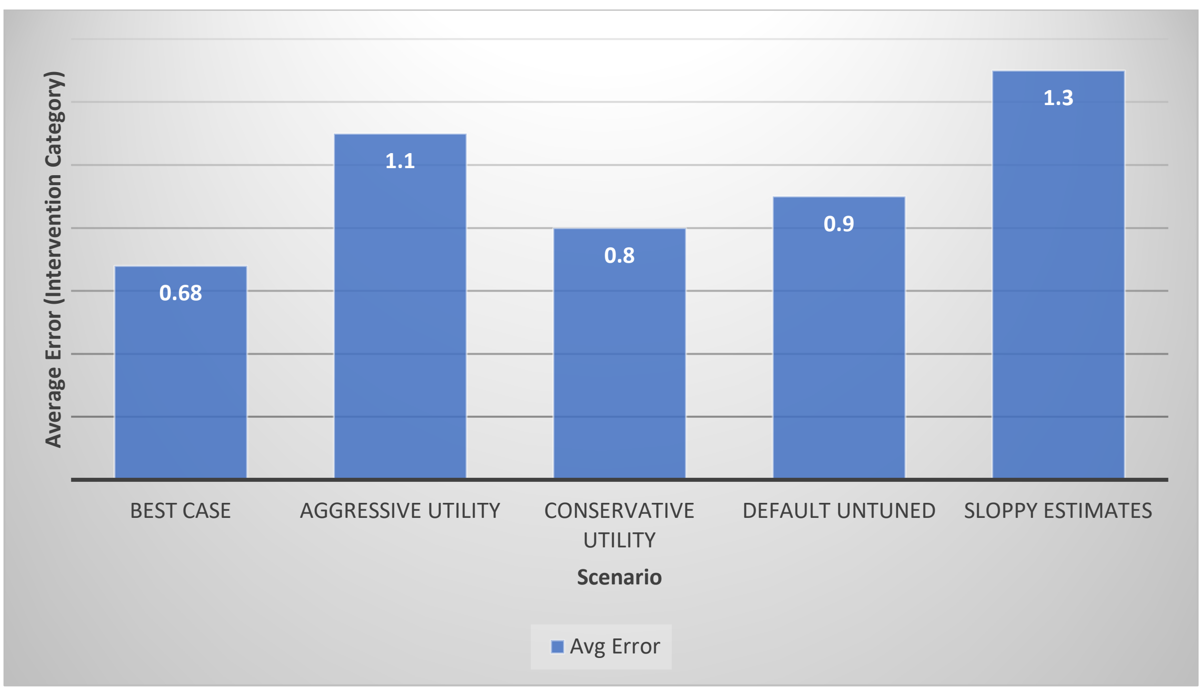

Figure 3-1. EUAC Sensitivity Chart

3.4. DISCUSSION AND IMPLICATIONS

The economic analysis presented in this paper highlights both the utility and shortcomings of LCC and EUAC methods when applied to infrastructure renewal decision making. Though further developed by empirical calibration and supplemented by spatial and societal risk extensions, several key insights and limitations emerge.

3.4.1. Value of Empirically Calibrated LCC/EUAC Models

The creation of a readable, modifiable spreadsheet model grounded in classical economic principles and scaled for utility has multiple advantages. When calibrated with real-world utility data, such as that from PIPEiD and WATERiD, the model demonstrates that proactive repair strategies (e.g., CIPP lining) consistently yield the lowest EUAC among other options. This supports the documented cost-effectiveness of trenchless technologies, consistent with WATERiD case studies that found up to 35% savings compared to full replacement (Welling and Sinha, 2014).

By incorporating societal costs and consequence-of-failure (COF) multipliers, it increases the model's decision-making ability. In high-risk contexts, these factors shift the relative rankings of strategies, aligning the results with risk-based asset management practices promoted by the EPA (2021) and Kleiner et al. (2006), (Sadiq, 2006). This tool offers a reproducible, clear tool for renewal strategy screening, being particularly convenient for utilities operating under financial or data constraints.

3.4.2. Limitations of Deterministic Frameworks

However, relying on deterministic cost modeling has its drawbacks. Simulation results from the calibrated spreadsheet model indicate that small variations in key assumptions, service life, and cost inputs, for example, can significantly impact EUAC outcomes. This variability becomes even more pronounced when spatial risk or operational uncertainty is introduced. While Monte Carlo simulations provide valuable insight into a project, they are only supplemental tests in this study rather than the core decision logic. As noted in infrastructure literature with a wider scope than just water utilities (Halfawy & Dridi, 2016), real-world degradation is highly stochastic, shaped by interactions among materials, environmental stressors, and interdependent feedback loops. Even when calibrated by field data, deterministic LCC/EUAC models struggle to fully reflect these dynamic behaviors, which is why an overreliance on simplified models for complex, high-stakes decisions raise concerns.

This limitation was quantified by a Monte Carlo simulation of 1000 iterations, where key inputs including discount rate (2-6%), failure cost ($20-$80k), O&M cost ($1-10/LF/year), and service life (50-100 years) were varied to mimic industry norms. Using verified data collected as part of PIPEiD EUAC only matched the recommended intervention 29.2% of the time with mean error being at 0.71. While no predictions were off by the maximum of 3, the model proved unreliable in choosing the proper renewal type, confirming that this manner of deterministic modeling was insufficient for use by water utilities, all of which enjoy little room for error in managing critical infrastructure. The error distribution is shown in Figure 3.2, and the EUAC error vs. the discount rate is shown in Figure 3.3. Both are valuable representations of the limitations of this methodology for choosing pipe renewal interventions.

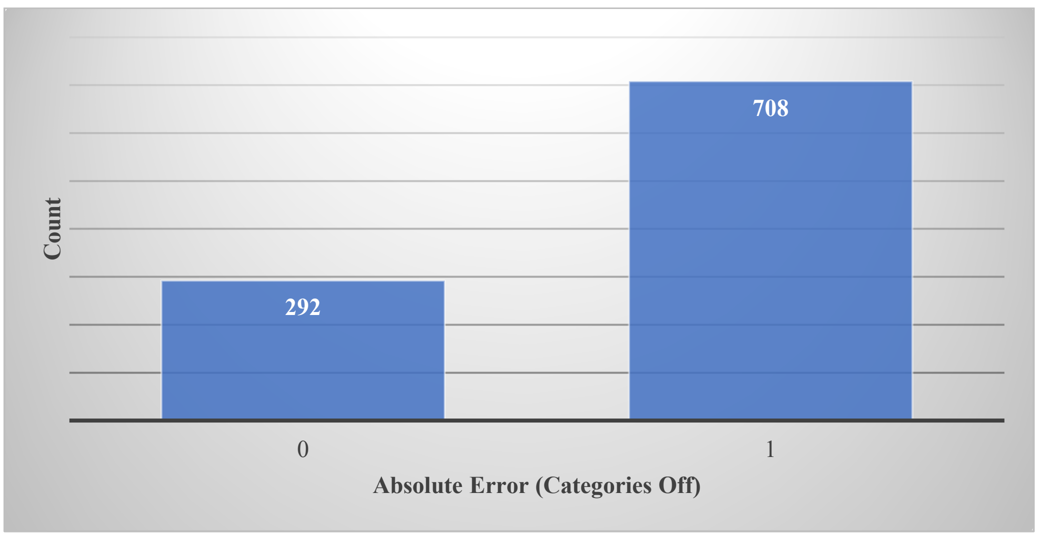

Figure 3-2. EUAC Model Error

The graph shows that the EUAC model was not accurate in 70% of the simulations, even with slight input variations, and only a minority of nodes were categorized properly.

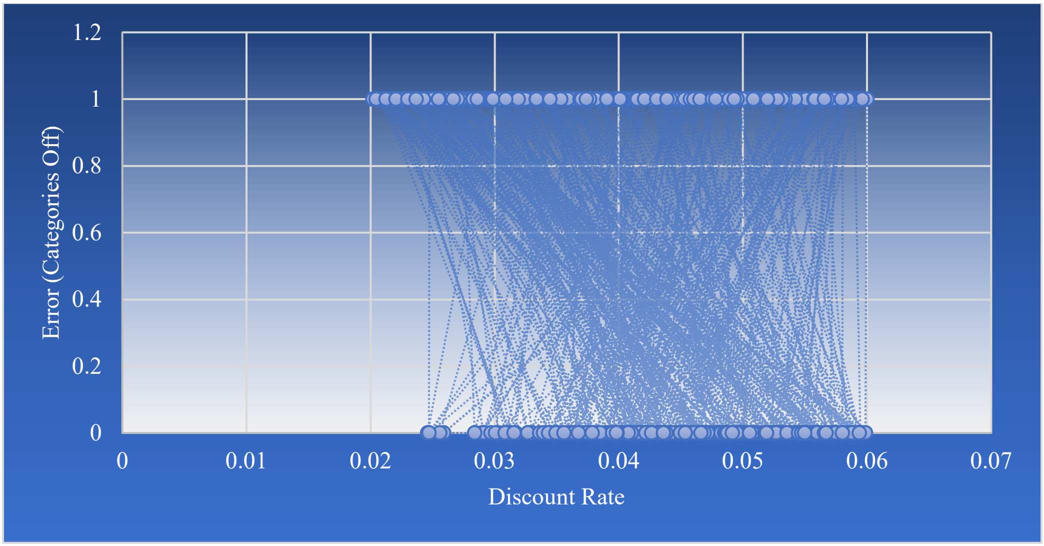

Figure 3-3. Error vs. Discount Rate Plot

The plot shows the volatility of the model with fluctuations in discount rate, where each line represents a slight difference in cost and service life. This results in misguided renewal activities, underscoring the need to better handle uncertainty in the analysis.

3.4.3. System-Level Constraints and Strategy Gaps

Another important limitation of deterministic models is their assumption of segment-level independence. In reality, pipeline segments operate within interconnected hydraulic and operational systems. Effective prioritization requires accounting for upstream/downstream dependencies, redundancy, and overall system criticality. While the current model does not capture such network effects, methods such as hydraulic modeling, graph theory, and GIS-based overlays have shown promise in more system-aware planning (Tran et al., 2020; Sægrov et al., 2014).

Additionally, the four renewal strategies considered (Do nothing, Inspect/Maintain, Repair, and Replace) do not reflect the full spectrum of available or emerging technologies. Innovations such as robotic inspection, AI-driven failure prediction, embedded sensors, and modular rehabilitation strategies have been gaining traction over the past few years. Although currently underrepresented in databases like WATERiD, incorporating these approaches into future analyses will be essential for advancing comprehensive asset management practices.

3.4.4. Implications for Utility Practice

For many utilities, especially those with limited data and technical capacity, the model provides a user-friendly platform for initial planning and comparative evaluation. It enables rapid scenario testing and localized cost customization. Despite these advantages, for utilities managing aging or high-consequence assets, more advanced tools are needed. Tools that would be able to take into account uncertainty, network interdependencies, and integrate non-monetary impacts.

The application of spatial risk weights and societal cost premiums, as adapted from Sekar et al. (2013), marks an initial step toward more intelligent decision support. Broader integration with GIS-enabled consequence mapping, real-time inspection data, and adaptive prioritization methods (e.g., fuzzy inference systems, machine learning) will also be critical components of this new model. These tools are analyzed in Chapter 4, which introduces a next generation planning framework based on Type 2 fuzzy logic. This model blends physical condition, economic performance, and spatial risk into a unified decision-support system, validated with data from three U.S. facilities.

3.5. CONCLUSION

This chapter demonstrated the value and limitations of applying empirically calibrated economic models to the problem of pipeline renewal planning. By integrating real-world cost data and service life distributions from WATERiD and PIPEiD into a user-friendly spreadsheet-based LCC and EUAC model, it became possible to generate strategy comparisons that better reflect actual utility experience. The results demonstrate the relative cost-efficiency of trenchless rehabilitation methods under typical conditions, while also showing how strategy ranking shifts when societal costs and spatial risks are taken into account. Despite the utility of this spreadsheet-based model, the analysis also revealed critical shortcomings. Even when calibrated with empirical data, deterministic models remain sensitive to small variations in input assumptions and often fail to capture the interdependent, uncertain nature of infrastructure systems.

Additionally, the limited strategy set used in this analysis excludes many of the innovative tools and predictive technologies emerging across the sector. As utilities face increasing fiscal and environmental pressures, decision-support tools must evolve to accommodate complexity, uncertainty, and localized risk. Chapter 4 builds directly on this foundation, introducing a novel Type 2 fuzzy logic system that integrates condition, cost, and spatial risk into a unified prioritization framework, offering a more nuanced and intelligent path forward for asset renewal planning.

Beyond properly leveraged financial data and extensive efforts into applying a deterministic model to a grossly dynamic testbed, the final effort was a model to direct decision making based on declining pipe performance and economic considerations resulting in a fuzzy-logic powered decision support model integrating physical and economic performance along with spatial awareness to help engineers prioritize interventions from "do-nothing", to inspection, and rehabilitation or replacement. Considering degradation with cost, location and time allows smart planning by optimizing intervention strategy and timing to capitalize on remaining useful life while lowering risk.

4. FUZZY LOGIC MODEL FOR METALLIC DRINKING WATER MAIN RENEWAL

4.1. INTRODUCTION

4.1.1. History of Renewal Models

Traditional deterministic modeling approaches are insufficient for accurate intervention planning due to the stochastic nature of water pipe failure dynamics, particularly when coupled with economic constraints that demand strict optimization of renewal expenditures across decades (EPA, 2002; Marlow et al., 2010). Conventional pipe deterioration models rely on empirical break rate analyses, and are often represented by Poisson or Weibull distributions to estimate failure probabilities over time (Kleiner & Rajani, 2010; WRF, 2011), (Loubier, 2021). These methodologies are inherently limited due to a dependence on historical break data that fails to capture mechanisms of degradation. The absence of a probabilistic cost-risk tradeoff model has resulted in infrastructure replacement schedules that either fall short or overdo capital investments relative to actual failure risks (AWWA, 2012). Fuzzy Systems, GIS, and financial optimization must be integrated in order to address these limitations.

The research involved a fuzzy logic-based probabilistic degradation model that synthesizes in situ degradation data, fuzzy inference rules, and GIS-based spatial prioritization into a renewal decision-support framework. Unlike binary threshold-based models, fuzzy logic enables dynamic, condition-dependent prioritization of renewal investments based on expert-defined rules and empirical trends. The framework was validated using Remaining Wall Thickness (RWT) analysis, historical failure data comparisons, and expert blind testing (WRF, 2018; EPA, 2002). By integrating GIS-based risk mapping and cost-driven prioritization techniques, this study developed a dynamic, financially optimized intervention framework that outperforms traditional renewal heuristics and is practical for municipal water utilities (AWWA, 2020). The research created a Type 2 fuzzy inference system renewal model that combines empirical deterioration modeling, geospatial analytics, and financial decision science into a predictive framework to adaptively balance water main physical and economic performance in determining appropriate intervention thresholds. This research builds on previous work using fuzzy logic as decision-support for infrastructure systems, e.g. type-2 fuzzy systems (Mendel 2007) and interpretive frameworks (Ross 2004).

4.1.2. Traditional Models and Prior Research

The evolution of decision-making frameworks in water infrastructure management has long been constrained by the rigid, deterministic nature of traditional asset renewal methodologies e.g. Equivalent Uniform Annual Cost (EUAC), Net Present Value (NPV), and Weibull-based probabilistic failure projections which relied on well-defined yet minimalistic assumptions regarding water main degradation, intervention timing, and economic feasibility (Kleiner & Rajani 2001; Deb et al. 2002; WRF 2009). In contrast, more advanced methods such as fuzzy logic inference systems and geospatial predictive modeling have been shown to ably handle uncertainty and with expert-driven rule systems to successfully govern water main renewal prioritization in real-world applications (Alegre et al. 2013; Ross 2004). While previous studies have utilized isolated applications of fuzzy logic for condition assessment, and some have incorporated deterioration modeling techniques for forecasting, few have synthesized these methodologies into a unified, financially oriented decision-support framework optimized for municipal water utilities (Kleiner et al. 2006; van Riel et al. 2014).

Managing water main infrastructure has traditionally depended on deterministic or semi-probabilistic models seeking to optimize the tradeoff between capital spends, operating and maintenance costs, and the estimated service life of the assets (Grigg 2005; WRF 2009). These approaches are helpful but are based on several assumptions that are too rigid to capture the system's complexity, uncertainty, and multi-causality. Current practices are grounded in condition assessment, failure history, and economic analysis; however, the models used are inadequate to incorporate dynamic inputs, stochastic failures, and the combined effects of environmental and operational stresses (EPA 2002; Burn et al. 1999).

The most common classic model used in financial decision-making is the Equivalent Uniform Annual Cost (EUAC), which estimates the costs of interventions over a planning horizon by annualizing the capital and operating costs. EUAC offers a clear path to choosing between renewal and repair, with the assumption of cost stability and clear intervention levels (Kleiner & Rajani 2001), yet, the model's limited by cost, failure rate, and discount rate assumptions which are very sensitive to variations in material performance, soil, and hydraulic deterioration (EPA 2017). Net Present Value (NPV) has also been widely applied to assess the economic feasibility of water main replacement and rehabilitation projects as a stream of costs and benefits of repair, replacement, and operating costs. However, it assumes that the deterioration of infrastructure is linear and that the time of intervention can be chosen optimally based on financial forecasts when in fact, the degradation of metallic water mains is a stochastic process that depends on various kinds of dynamic environmental interactions e.g. hydraulic loading and corrosion (Alegre et al. 2013).

Weibull distributions are also commonly applied in order to determine failure probabilities of pipes and determine mean times to failure, where shape and scale parameters can also be used to describe the distribution of failure rates (Deb et al. 2002; WRF 2016). This approach is better than the deterministic models as it includes failure probabilities, but it has the sizable restriction of using historical failure data which may not adequately represent a project's specific conditions, materials and loading including traffic and soil movement (Rajani & Kleiner 2004). Another popular approach is the break-rate based replacement approach, which assumes any pipes that reach a failure rate cap should be replaced. This approach is used by utilities that have a reactive renewal policy, and the replacement standards are based on the frequency of breaks within a certain time frame (Marlow et al. 2010; WRF 2015). However, break rates do not capture other degradation processes, including internal corrosion, external mechanical loading, and operational changes that can increase the failure propensity despite the breakage number. Traditional water main management models are unable to incorporate uncertainty, expert knowledge, and multi-criteria decision making into their decision-making process; their stochastic or single-objective based mechanics do not capture the interdependency of the deterioration processes (Burn et al. 2010). Additionally, they are unable to incorporate spatially correlated data sources such as environmental conditions from GIS, real-time hydraulic data, or NDE data.

4.1.3. Fuzzy Logic for Water Main Infrastructure Management

The development of asset management strategies for water pipeline infrastructure has led to a need for more sophisticated analytical frameworks that are able to capture the stochastic nature and nonlinearity of the pipeline degradation process (Burn, 2010; Sgro, 2006; Marlow, 2013; Kang, 2008). The most significant innovative techniques identified in the recent past include fuzzy logic which is a systematic approach to handling imprecise, vague and non-linear relationships between various factors that affect pipeline performance (Zadeh 1965; Ross 2004; Butry et al. 2014). Conventional approaches are based on deterministic descriptions of the input-output relationships, which do not adequately describe the stochastic nature of the environment, loads, and material loss (EPA 2002; WRF 2015).

In contrast, fuzzy logic-based models describe an inferential calculation strategy that incorporates expert judgement, probabilistic evaluation and real time data for better decision making in renewal (Kleiner et al. 2006; Lins and Lins 2014). Fuzzy logic systems were proposed by Zadeh in 1965 and are based on the concept of fuzzy sets which allow variables to be classified into grades rather than two distinct categories. This property is especially useful in infrastructure applications where the criteria such as RWT, internal corrosion rate, soil corrosion potential and break frequency etc. do not have clear cut off points but rather grade into each other in a gradual manner between good and poor conditions (Moselhi and Osman 2003; Zhang et al. 2016). Fuzzy inference systems (FIS) use membership functions that describe linguistic evaluations (e.g., 'low,' 'moderate,' or 'severe' deterioration) to express complex engineering judgments as quantitative decision rules that support setting priorities (Ross 2004; Marlow et al. 2010). The main strength of fuzzy logic models in pipeline management is the ability to combine various types of information including historical break frequencies, costs, soils and fluids properties and other parameters without making strong assumptions about the parameters (Burn et al. 1999; Al-Barkawi and Zayed 2008). Traditional regression based or probabilistic models require specifying failure distributions whereas fuzzy logic allows for online learning by expressing expert knowledge-based rules of deterioration tendencies in the real world (Najara et al. 2006; Liu and Kleiner 2013). This enables the development of more robust decision support tools that are not dependent on strict statistical relationships or sufficient number of samples, and thus suitable for application to the management of aging and diverse water distribution systems (Kleiner and Rajani 2010; WRF 2013).

Recent developments in fuzzy logic-based models have employed Type 2 fuzzy systems which are more sophisticated than the conventional Type 1 frameworks (Mendel and John 2002; Hagras 2007). Type 2 fuzzy logic addresses uncertainty in the form of expert knowledge, data measurement error, and spatial variability, which makes it suitable for applications such as infrastructure management where input data may be missing or inaccurate (Gong et al. 2012; Alani et al. 2014). The Type 2 fuzzy set has one additional level of uncertainty over the Type 1 fuzzy set, and this extra level of freedom enhances the pipeline condition assessments, allowing it to reduce the likelihood of being over-reliant on deterministic information (Mendel 2007; Wu and Mendel 2009). Furthermore, the combination of fuzzy logic with spatially enabled data including GIS layers has allowed the real time visualization of the condition of the pipelines and the need for intervention (Halfawy et al. 2008; Koo and Ariaratnam 2008). The GIS fuzzy hybrid models have been applied to spatially allocate failure probabilities, costs of intervention, and multi criteria risk analysis to help utilities make decisions on the most affected assets (Fenner et al. 2000; Halfawy and Newton 2011). This spatial integration is most important in the pipeline networks especially in the urban areas where the environmental conditions such as soil, traffic loads and objects in the vicinity affect the rate of corrosion (Alegre et al. 2013; WRF 2016).

It is therefore possible to improve the current fuzzy logic-based asset management systems to include GIS in order to shift from the traditional approach of renewal to risk-based management (Kleiner et al. 2006; Grigg 2013). Latest developments have integrated fuzzy logic with machine learning algorithms, which combine neural networks, genetic algorithms, deep reinforcement learning and fuzzy inference, however only rule-based fuzzy logic was employed (Tran et al. 2017; Mounce et al. 2014). For future advancements, hybrid models can update the models online using real-time failure data, condition monitoring information, and reinforcement learning of intervention strategies (Koppel et al. 2016; Wu et al. 2020). The proposed fuzzy models are trained using historical and real time pipeline performance data and hence, the membership functions and the inference rules are optimized to enhance the prediction capability and cost effectiveness in pipeline replacement planning (Butry et al. 2014; Zayed and Al-Barqawi 2010). However, there are some problems in the complete implementation of the fuzzy logic-based pipeline management systems. Perhaps the most important limitation is the expert fine-tuning requirement since the construction of membership functions and the rule base is usually knowledge-based (Mendel and John 2002; Hagras 2007). Moreover, the significance of fuzzy logic models in regulation and finance is currently an active area of study, especially in regard to the integration of data analysis and policy-making with respect to the trade-off between optimization and policy-making (EPA 2017; Grigg 2014). However, as the computational resources and the amount of data are constantly increasing, the role of fuzzy logic in infrastructure management will only grow, greatly helping utilities in the management of aging water pipeline systems (WRF 2015; Marlow et al. 2013). Fuzzy logic was proposed as the basic theory for combining the financial costs, condition-based deterioration models and spatial risk ranks to form a single decision support system. This study therefore went beyond the previous works to further the state of the knowledge in pipeline asset management by showing how the use of fuzzy inference systems can enhance the conventional replacement decision making processes in terms of flexibility, accuracy and costs. Recent studies (Tran et al., 2020; Wu et al., 2023) apply deep learning to pipeline degradation, still fuzzy logic remains a strong choice for municipal decision-makers requiring defensible and transparent methodologies. The model addresses a critical gap in prior research by capitalizing on fuzzy logic's strength in handling degradation uncertainty while integrating financial optimization.

Due to the scale and complexity of managing large scale water distribution networks, it is necessary to have an analytical framework that can simultaneously quantify degradation uncertainty, incorporate financial constraints and dynamically prioritize interventions (Kleiner and Rajani 2010; Burn et al. 2010; WRF 2015). At present, conventional asset management paradigms which are based upon deterministic failure models and rigid ranking-based prioritization schemes are not capable of providing the flexibility and responsiveness that are required for modern infrastructure governance (Marlow et al. 2013; Grigg 2013). The integration of fuzzy logic with a financially-structured pipeline renewal framework as presented in this paper is a shift in decision science that enables the adaptive reallocation of capital resources while maintaining structural integrity across multi decade planning time horizons (Koo and Ariaratnam 2008; Butry et al. 2014). Up to now, the role of financial modelling in pipeline asset management has been limited to cost benefit analysis that are used as secondary constraints, not as primary decision makers (EPA 2017; Alegre et al. 2013). This research re-positioned financial parameters from being passive evaluation factors and used them as active factors in determining intervention priorities when incorporated into the fuzzy logic inference structure (Al-Barqawi and Zayed 2008; Wu et al. 2020). Fuzzy models have conventionally focused their main concerns on the quantification of structural failure probabilities; however, the model was transformed into an economically active decision-making system, where financial viability, cost aggregated risk exposure and opportunity loss are the drivers of intervention decisions (Fenner et al. 2000; Mendel 2007). One of the key contributions was the integration of spatially distributed cost prioritization algorithms whereby economic factors including repair cost schedules, consequences of deferring maintenance, and the fiscal consequences of consequent pipeline failures were programmed into the decision hierarchy of the model (Ross 2004; Zayed and Al-Barqawi 2010). Traditional geospatial mapping techniques are not as sophisticated as this method which uses cost weighted spatial intelligence to derive geographic capital deployment strategies that are consistent with changing financial circumstances (Halfawy et al. 2008; WRF 2016). The end product is a financially integrated, high fidelity decision support system that presents a novel paradigm for long run infrastructure expenditure (Grigg 2014; Marlow et al. 2010).

4.1.4. Previous Research in Fuzzy Logic-Based Pipeline Renewal Models

The use of fuzzy logic frameworks in pipeline asset management has historically been limited to static rule-based systems where the urgency of an intervention is a function of failure risk assessments that are made and are relatively insensitive to real time data (Zadeh 1965; Al-Barqawi and Zayed 2008). Such systems have been deterministic and therefore unable to adapt their decision thresholds dynamically as a function of changing economic conditions, break rates, or observed degradation trends (Kleiner and Rajani 2010; Burn et al. 2010). This effort solved these challenges by developing a novel dynamic feedback loop that adapts fuzzy inference rules using real world financial and structural performance data (Wu et al. 2020; Mendel 2007). The main weakness of the current approaches to infrastructure renewal is that they are static and are based on the assumption that intervention requirements are determined by historical average rates of deterioration and not by condition-based management (Alegre et al. 2013; WRF 2016). The model ensured that intervention sequencing was fluid, operationally-attuned and economically-optimal by integrating dynamically recalibrating, cost-reflective fuzzy logic decision systems (Ross 2004; Zayed and Chang 2002).

The research combined historical failure records, stochastic models of future maintenance costs, and condition adaptive renewal decision-making to create adaptive systems of infrastructure governance that go beyond the limitations of deterministic models (Koo and Ariaratnam 2008; Grigg 2014). Furthermore, the design presented an economically weighted decision architecture integrated with GIS, where spatially resolved cost functions, quantified variation in expenditures across the spatial domain, and regional budgetary constraints are integrated into a single decision-making framework for renewal scheduling (Halfawy et al. 2008; Fenner et al. 2000). The research further presented an improvement on conventional GIS-enabled asset management systems that operate as static risk mapping tools (WRF 2015; EPA 2017). Geospatial analysis was converted into a financial intelligence tool that is capable of assisting in the alignment of infrastructure investment with changing cost estimates while taking current operations into account (Marlow et al. 2013; Butry et al. 2014). The result of this approach was a geographically- and financially-synchronized renewal prioritization framework that achieves optimal capital utilization for the maintenance of infrastructure over planning horizons that span decades (Raad et al. 2022; Kleiner et al. 2006).

4.1.5. The Evolution of Pipeline Asset Management Theory

The methodological advancements introduced alter infrastructure renewal science in a manner that sets financial optimization as a core determinant of intervention prioritization rather than leaving it as a secondary constraint (Butry et al. 2014; WaterRF 2013; EPA 2017). This research went beyond the limitations of structurally deterministic failure models by proposing a multi-tiered decision architecture that integrated economic, operational, and structural data into an adaptive, self-calibrating renewal prioritization engine (Ross 2004; Kleiner and Rajani 2010; Wu et al. 2020). These contributions are, therefore, central to this study and have shaped the development of a financially smart infrastructure renewal approach and the definition of a new standard for decision making for condition based and cost-effective infrastructure management in a world of increasing infrastructure demands.

4.2. METHODOLOGY

4.2.1. Model Architecture and Data Support

Water main renewal planning requires a sound framework driven by transparent and acceptable practice while maintaining adaptability in light of uncertainty in degradation and finance. Current asset management approaches are deterministic in failure modeling and have static capital planning approaches that are unable to capture the stochastic nature of pipeline deterioration and financial interdependencies involved (Burn et al. 1999; Rajani & Kleiner 2001). The research addressed these limitations by developing a financially integrated decision support system using a Type-2 fuzzy inference system, economic consequence analysis, and spatially assisted intervention selection process (Mendel 2001; Ross 2004; Kabir et al. 2015). Water pipeline networks—as engineered systems which are exposed to long term environmental conditions, varying loads during service, and material degradation mechanisms are not equally predictable in their failure behavior and cannot be modelled deterministically (Folkman 2012; Kleiner & Rajani 2010). The developed model architecture is shown in Figure 4.1.

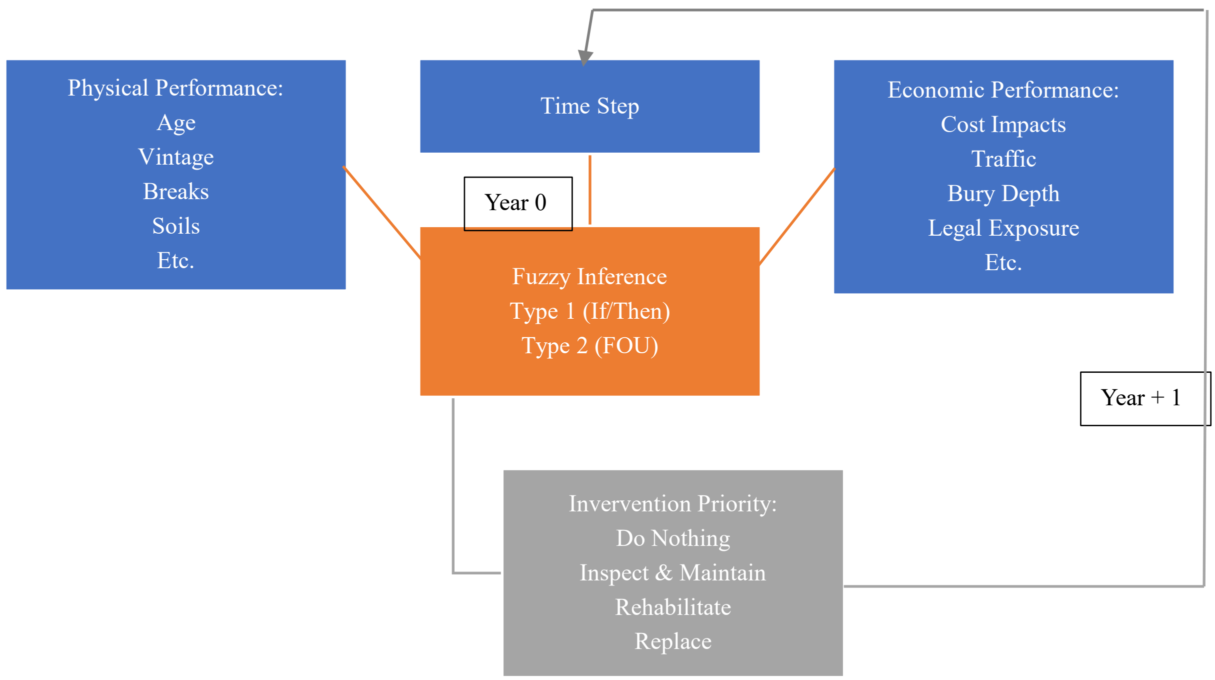

Figure 4-1. Fuzzy Model Architecture

The reliability of any predictive model is a function of the strength, comprehensiveness and temporal continuity of the data on which the model is based (Alegre et al. 2013). The research solved these structural deficiencies by proposing a unified data ingestion pipeline incorporating failure history, geospatial, environmental, financial, and operational performance data to support the decision-making process. Longitudinal failure data was incorporated into the database in a structured manner to supply the empirical calibration of the degradation inferencing engine. Geospatial overlays of soil corrosivity, hydrodynamic, and weather indices enabled the model to include consideration of geo-spatial prioritization of renewal investments. Financial data streams representing repair cost distributions, capital expenditure trends, and inflation adjusted replacement costs allowed for real time economic consequence mapping. This allows intervention prioritization to be repeatedly adjusted against the background of changing budgetary conditions as part of a computationally cohesive system, where renewal prioritization is based not only on structural integrity projections but also includes the vital factors of financial feasibility assessments and geospatial risk weighting. The various parameters chosen to drive the fuzzy logic model were selected based on the literature review, practice review, and ease of sourcing data for the participating utilities. The parameters were grouped according to their influence on the physical and economic pipe performance, ensuring an effective marriage of technical strength and practicality. The research built on previous work by incorporating physical performance predictors (e.g., RWT, break counts, traffic loading) and integrating them with economic performance components within a fuzzy logic-based, GIS supported tool.

4.2.2. Performance Parameters

The fuzzy model incorporates both physical and economic performance indicators (Tables 4.1-4.2) selected based foremost on expert guidance, and then availability/quality.

Table 4-1. Physical Performance Parameters

Table 1. Physical Performance Parameters	
Structural Integrity	Pipe Age
	Pipe Material
	Pipe Break
	C Factor (Tuberculation)
	Remaining wall thickness
Internal Condition	Water quality (Aggressive Index)
	Water temperature
	Pressure
	Adequate Fire Flow
	Customer complaints
	Lining Type
External Stress	Flooding Frequency
	Drainage Class
	Particle Size
	Buried Depth
	Subsurface Temperature
	Traffic Loading
External Corrosion	Water Table Depth
	Ground water fluctuation
	Soil Corrosivity for steel
	Cathodic Protection
	Stray Currents
	Coating Type

Table 4-2. Economic Performance Parameters

Table 2. Economic Performance Parameters	
Direct Financial Impact	Asset Replacement Cost
	Break Repair Cost
	Inspection/Condition Assessment Cost
	Cost of Water Loss
Operational Financial Impact	Increased Maintenance Expenditure
	Pumping and Treatment Cost Increase
	O&M Budget Overrun
Indirect Financial Impact	Property Damage Liability
	Road/Rail Traffic Disruption Cost
	Environmental Restoration Expenditure
Environmental/Legal Costs	Regulatory Compliance Cost
	Litigation and Legal Settlement Expenditure
Service Disruption Costs	Emergency Service Disruption Cost
	Customer Compensation Payment
Asset Management Metrics	Expected Revenue Loss
	SLA Violation Penalty
Future Financial Exposure	Early Replacement Cost
	Downtime Due to Spare Part Shortages

4.2.3. Renewal Intervention Modeling

The stochastic nature of pipeline deterioration requires an analysis framework capable of translating imprecise, partial, and temporally varying condition data into failure probabilities. The fuzzy inference system was developed to include membership functions utilizing each critical variable based on observed structural failure modes, using tuned membership functions and rules to represent how each factor behaves in the field along with how they interact, enabling a realistic model of ground truth pipe performance. The computational inferencing mechanism ensured that risk assessment is relevant with respect to changing conditions, which in turn allows operators to change intervention plans before failure probabilities become unacceptable.

This study is the unique in that it presented an economically integrated renewal prioritization model where failure consequence weighting is directly quantified by financial exposure metrics, embedding cost implications into intervention planning rather than considering them as external. The economic optimization framework used a two-tiered calibration mechanism that maps immediate break repair costs against projected future capital expenditure trajectories to enable prioritization according to long-term financial risk exposure. This ensures that renewal decisions are not only structurally justified according to failure likelihood, but also maintain financial optimization to avoid reactive intervention cycles that are driven by short-term budgetary limitations at the expense of escalating long-term liabilities. The final framework and methodology for the intervention fuzzy modeling can be seen in Figure 4.2.

Figure 4-2. Renewal Intervention Fuzzy Model Architecture

Figure 4.3 shows how the model prioritizes interventions over a designated planning window, one hundred years in this case for a 20-inch cast iron main installed in 1965 as part of a large Midwestern utility. The plots demonstrate the informed response of the fuzzy system as it weighs in situ pipe and economic performance over time. The vertical axis represents the renewal intervention priority on a 0–1 scale, while the x-axis represents time. An intervention priority is tripped by crossing the Do-Nothing plot, whereby action is taken and the model resets to reflect the updated parameter scores owed to the intervention. The model dictates that the pipe should have been inspected/small repairs made at this stage in its life. As can be seen by the intersection of the blue and orange plots (replacement and "do nothing" intervention priorities respectively), the pipe should be replaced in year 11 in order to maximize life cycle cost and to minimize catastrophic risk of failure. The pipe is then replaced accordingly and the priority scores then reset accordingly in an intuitive way, for example the priority of "do nothing" is maxed out while the priorities to perform any active interventions are minimized and then grow over time as dictated by the model based on key parameters such as groundwater fluctuations, traffic loading, pressure, etc. that drive pipe useful life. In this way the effects of physical performance and economic health over time are more tangible for utility managers whereby enhanced decisions can be readily made.

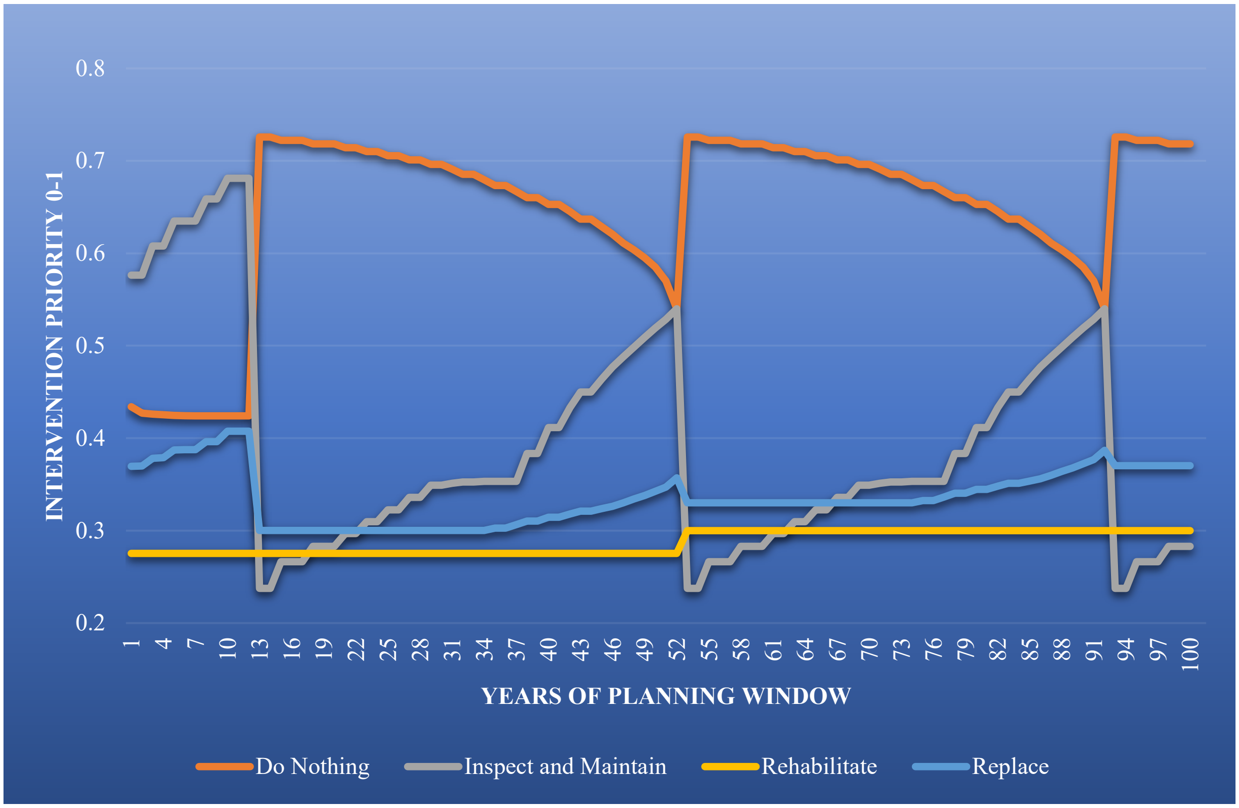

Figure 4-3. Renewal Intervention Fuzzy Prioritization over Planning Window

It is important to note that often the model would suggest performing an inspection. This is especially important in pipe segments where constructability is a challenge, pressure transients are a possibility, and other similar areas where knowing the condition of the pipe at regular intervals becomes critical to proper, proactive management. While the model is currently tuned to say that once an inspection occurs and any point repairs are made the pipe is then restored to a more initial, low-risk condition, this is not a foregone conclusion. If in fact it is determined through the inspection another course of action is more advisable (rehabilitation or replacement) through industry best practices, the utility would then act accordingly and the model would then reset to reflect a brand-new pipe as shown in Figure 4-4.

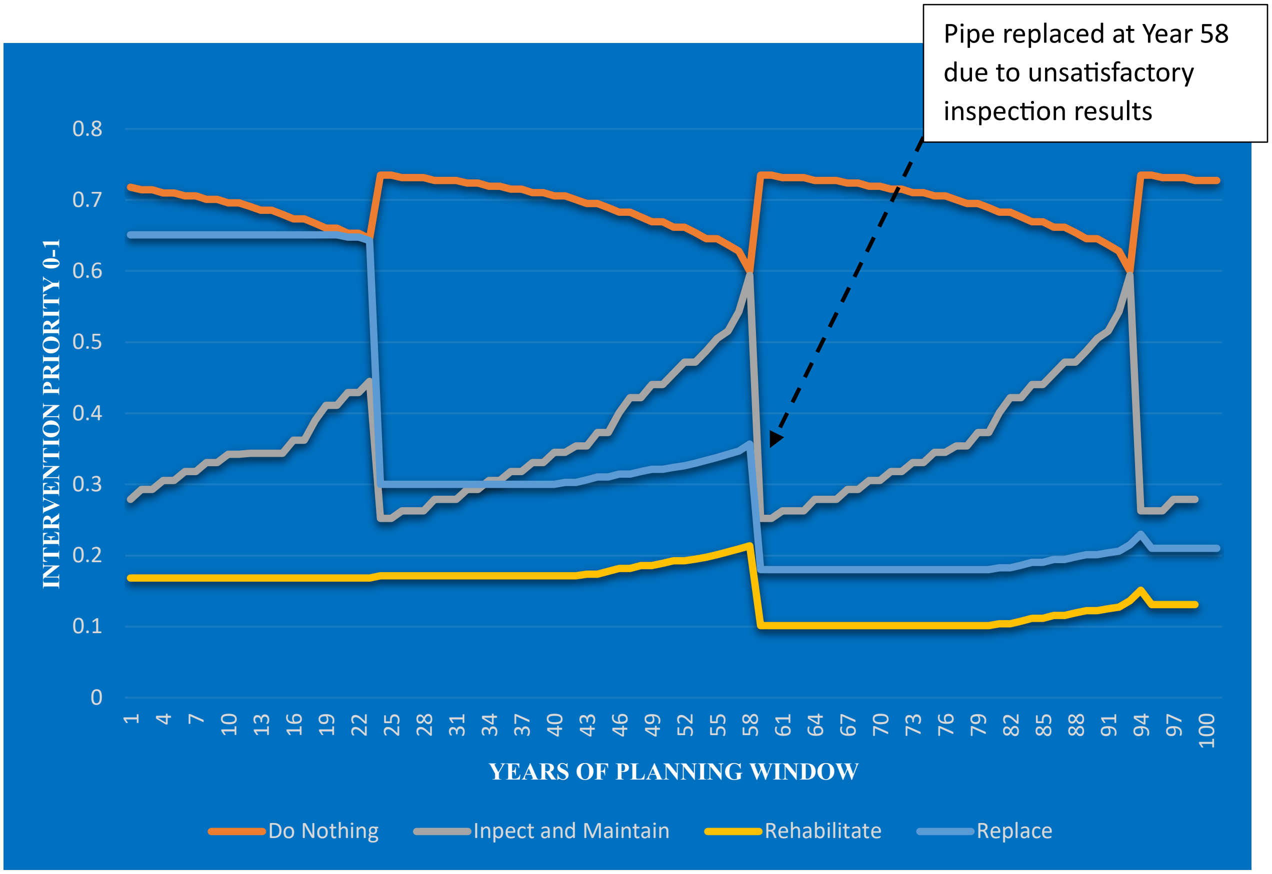

Figure 4-4. Pipe Replaced due to Inspection Findings

A weighting convention, as shown in Appendix A Table A2, was used to ensure that the modeling efforts took greatest advantage of the various data sources while also accounting for uncertainty. Weights were assigned according to the quality of the data and then tested against ground truth data received from the participating utilities, including RWT and repair records. The calibration involved manually adjusting fuzzy rule weights until the greatest level of accuracy was achieved in matching the intervention recommendation per industry standards.

240 Fuzzy rules were developed in the same manner, and a Gaussian smoothing function implemented to avoid overfitting by methodically tweaking outputs into the smooth curves that would be found were the model perfectly tuned thereby handling all values successfully. Rule addition beyond this was found to decrease model precision and prediction value. The input weightings reflect modeling confidence gained by ample documentation of physical verification and timely updates, e.g., parameters such as Remaining

Wall Thickness (RWT) and Pipe Break frequency with extensive metadata. Conversely, parameters derived though web searches and industry averages were given lesser weights. GIS played a major role in ensuring the quality of data remained high via extensive overlays to identify trends, successfully match key attributes to the relevant pipe nodes, as well as to verify utility records against national datasets. These outputs then add great value in supporting the eventual decision science phase of the work.

The study developed a geospatially embedded financial optimization model that integrated dynamically-calibrated renewal timing with structural degradation risk. The framework developed financially weighted risk distributions and directed interventions when degradation likelihood, consequence severity and financial feasibility demanded it. Renewal decisions are then optimized by location to ensure intelligent capital allocation while concurrently limiting physical and economic risk exposure. An example of the outputs of the model can be seen in Figure 4.4 where fuzzy priority scored-pipes are contrasted with one of the most notorious failure drivers—soil corrosivity. Darker segments correspond to more critical interventions (rehabilitation or replacement), while darker colors in the corrosion mapping signify more troublesome zones for metallic pipes. This map supports efficient condition assessment and renewal project grouping, representing just a small example of valuable decision support.

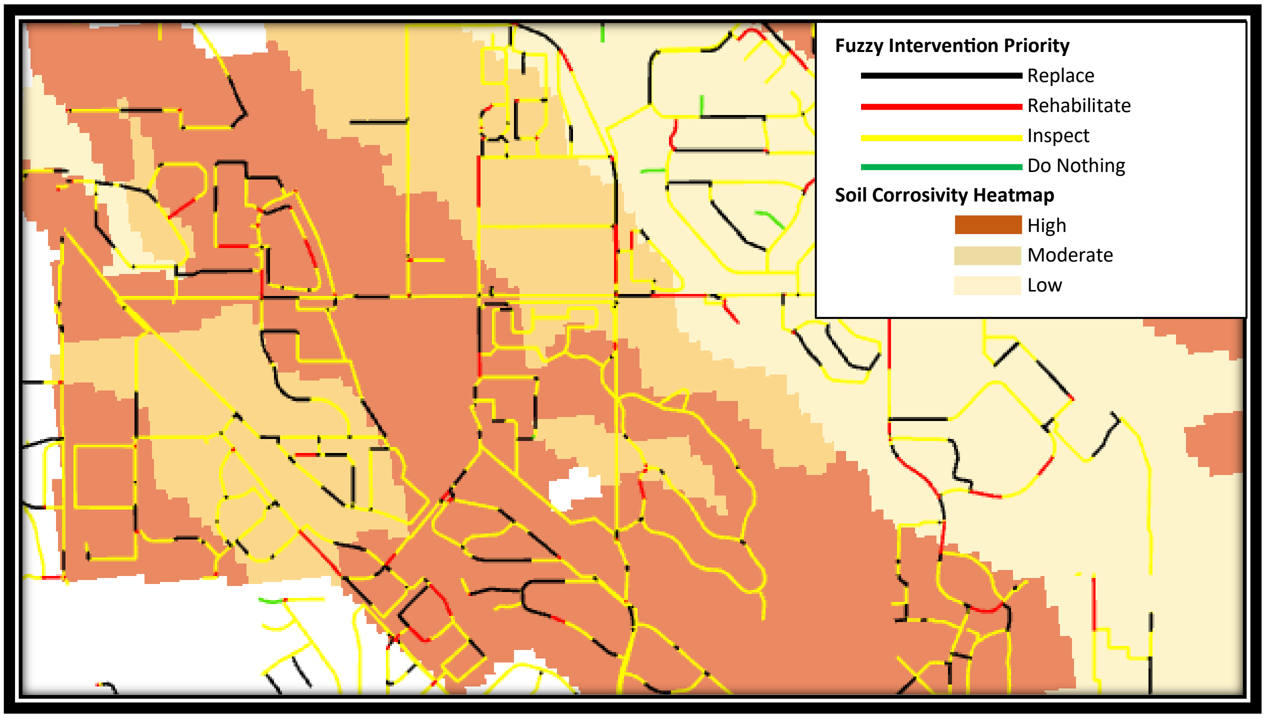

Figure 4-5. Fuzzy Priority Scored Pipes with Corrosivity Choropleth

The study began with an oversimplified and eventual full-scale Type 1 fuzzy model built to prescribe renewal type selection and timing based on failure likelihood and economic consequence. Validation uncovered discrepancies between expected and observed performance due to the Type 1 model's inability to properly handle edge cases and instances with inconsistent break and RWT records. Consequently, the model was tested as a Type 2 fuzzy inference system which employed additional groupings in its membership functions, hence better handling input variability. The resulting model was more robust yet preserved the interpretability and transparency of the original model, offering improved and more defensible prediction performance. Appendix A Table A3 summarizes the distinctions between the Type 1 and Type 2 fuzzy inference systems observed.

4.3. MODEL VALIDATION

4.3.1. Utility Records and Ground Truth Data

The strength of a predictive asset management framework depends on how closely it models deterioration, and how effectively it informs the timing of interventions. The credibility of the financially embedded fuzzy renewal decision model was established by subjecting it to a rigorous, multi-tiered validation process that included historical failure records, real time field assessments, probabilistic sensitivity analysis, and comparisons with similar models in the industry. The core objective of this validation exercise was to determine if the model's projected failure probabilities were consistent with known failure methods and timing thereof in an empirically defensible manner. The validation methodology (Figure 4-6) involved comparing model outputs to historical break records and remaining wall thickness data provided by participating utilities. The analysis relied on the practical, case-based evaluation among various pipe types and environments instead of using advanced statistics. By comparing model intervention suggestions to expert expectations (utility workshops and historical renewal records), the model was shown to behave in a consistent and defensible manner. This form of ground truth comparison solidified the model's utility as a decision-support tool in current and future management work.

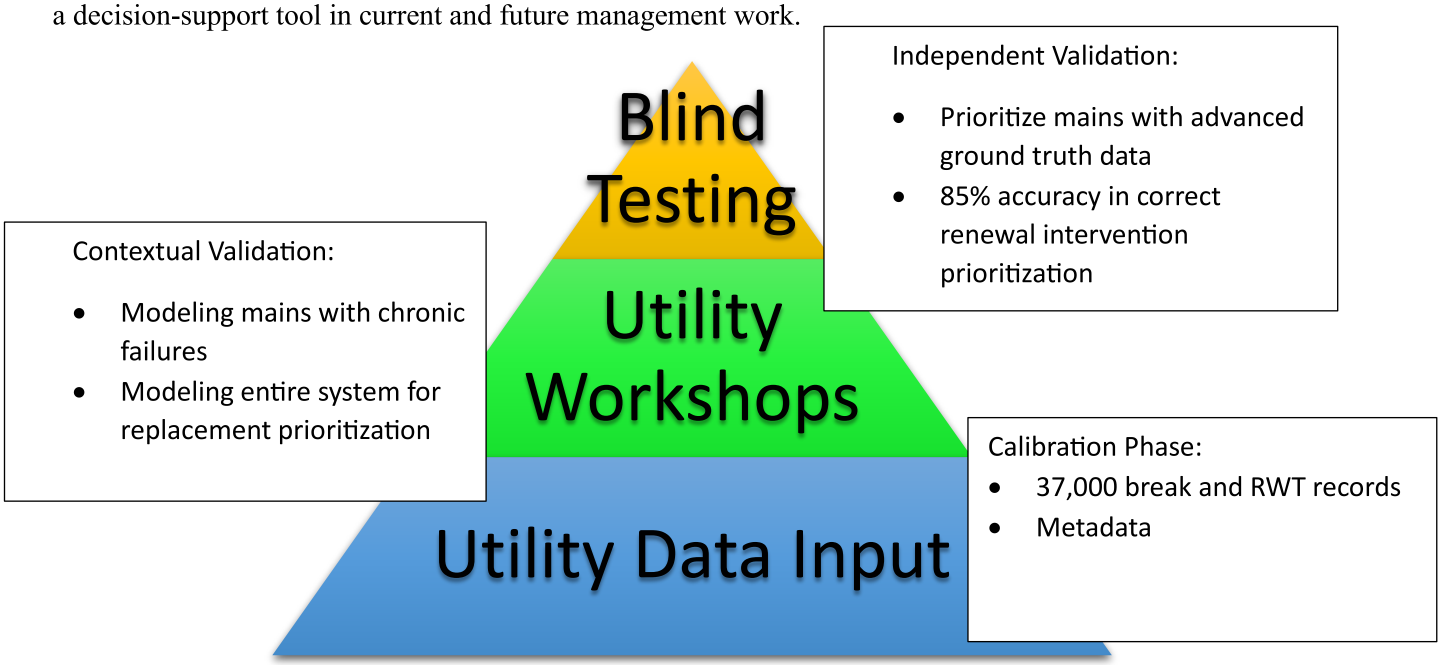

Figure 4-6. Model Calibration/Validation Process

Initially the model was tuned and calibrated using break history from three participating utilities spread across the US (Western, Midwestern, Eastern). Uniquely, suspected inconsistencies, outliers, and pipes with missing data were intentionally left in the analysis to better model the real world where these are common issues. In this manner the fuzzy model was stress tested against noisy data while outputs were highly scrutinized for their stability and alignment with observed utility best practices. Robustness in modeling outweighs perfection and hence this was the approach taken (Kleiner et al. 2010). The model was calibrated on these nearly 37,000 failure records until it had reached over 80% accuracy. Further model refinement was then performed comparing model outputs to the hundreds of empirical remaining wall thickness (RWT) records and recommended renewal activity based on guidance from AWWA M77 and M28. This refined the model further, increasing accuracy to nearly 87% in choosing the proper intervention, with recall of 0.83 and an F-1 score of 0.85. The model was also tested by removing 10% of the critical parameters such as RWT or break history and still maintained a mean absolute error below 0.15, reinforcing its strength and applicability. Of critical importance, the model was not calibrated blindly on legacy, less-effective practices, rather, only on the records from the most advanced, highly respected utilities in the industry, selected by their reputation as leaders in asset management, quality of records, and transparency. These included both public and private entities exhibiting industry-leading results with large service areas and strong renewal planning. Further, the calibration only occurred on records matching best practices as defined by AWWA and leading consultants. This approach ensured that the model maintained its empirical grounding while avoiding improper tuning. The marked results of the utility workshops and blind testing verified the effectiveness of the approach.

The model tested positively in its ability to outperform traditional deterministic ones in prediction accuracy, risk avoidance (as shown in Table 4.3), and in overall reduction of life cycle cost (Table 4.4). Further, the model reduced ill-timed pipe replacements by 27% and catastrophic failures by 15% as compared to the break-rate methodology and achieved a prediction accuracy of 85% when classifying pipes per their next prescribed renewal intervention based on complete ground truth. This was supported by the recall of 0.83 and F-1 score of 0.85 as explained earlier, showing the model's robust abilities at guiding water main management activities.

4.3.2. Sensitivity Analysis

A sensitivity analysis was then conducted to review the effects of uncertainties in key input variables on the model outputs: risk score and life cycle cost (LCC). Hundreds of simulations were run with input variations to determine the high impact factors that affect model predictions. This ensured that small input fluctuations did not disproportionately affect renewal prioritization decisions, thus ensuring the operational stability of the model under real-world conditions. The model remained stable during further calibration, without unwarranted variations. This sensitivity analysis confirmed the fuzzy logic framework to be robust, adaptable, and resilient in making justifiable recommendations for renewal prioritization across the range of pipeline conditions. The results of the testing can be seen in Appendix A Figures A4-A5. Traffic Loading and Pipe Material drove risk prioritization and LCC outcomes the most, followed by Workforce Availability, Road Traffic Flow Impact, and Water Quality-Related Inputs. This confirms the relevance of the model where these parameters often govern pipe physical and financial performance. Risk score standard deviation was calculated by altering each input over ±20% range, confirming the primary drivers in metallic water main performance.

To verify the practical applicability of the framework it was compared with traditional structural modeling such break-rate replacement heuristics, EUAC-driven intervention scheduling, and conventional Weibull hazard modeling. This comparative performance assessment was structured around three core evaluation metrics:

1. Risk Mitigation: Defined as the standard deviation of the errors between the real and predicted failure probabilities, with statistical comparison based on root-mean-square deviation (RMSD) and normalized mean absolute error (NMAE) scoring as seen in Table A6. Tables 4.3-4.4 show the fuzzy model

consistently outperformed the competing models across the case studies in risk mitigation and cost savings.

Table 4-3. Average Risk Score of competing models over 100 years

Model	Average Risk - West Coast	Average Risk - Rocky Mountains
EUAC	22	21
Fuzzy	**7**	**8**
Nessie	10	9
KANEW	9	10
Waverider	11	12
Break rules	13	14

Table 4-4. NPV of competing models over 100 years

Model	NPV LCC - West Coast ($)	NPV LCC - Rocky Mountains ($)
EUAC	-300000	-200000
Fuzzy	-700000	-100000
Nessie	-1200000	-600000
KANEW	-1300000	-700000
Waverider	-1000000	-600000
Break rules	-400000	-400000

2. Economic Efficiency: Evaluated by means of comparative capital expenditure simulations over a 50-year planning horizon, whereby the financial effects of the proposed framework were compared to traditional approaches using discounted cash flow (DCF) analysis and net present value (NPV) differentials.
3. Timing Optimization: Assessed by the model's ability to avoid both premature replacements and catastrophic failures, ensuring life cycle cost limits and risk thresholds were not exceeded in the planning window.

The benchmarking results showed that the proposed model typically outperformed all the conventional methodologies in example evaluation dimensions. It reduced capital expenditures by more than 18%

compared to EUAC-based scheduling, and reduced early replacement by 27% and catastrophic failures by 15% relative to break count replacement heuristics.

In addition to internal validation and comparative benchmarking, the model was subjected to a blind validation process using independent and previously unseen utility datasets. This was accomplished in partnership with three external agencies, two in multiple collaborative sessions where specific instructions were given to test the model in a way that showed its merits in tackling their most challenging current situations, and one with an anonymized municipal water agency who supplied proprietary pipeline failure records in the context of anonymized conditions. In the workshops the experts engaged were given the model results and confirmed that the model showed strong correlation with their most informed recommendations. Similarly, in the blind testing, the model was calibrated only on its training dataset, and the outputs were then compared retrospectively to real world failure occurrences within the blind dataset to determine its generalizability and predictive resilience. The results of the study, represented in Appendix A Table A7, showed that the model maintained its predictive capability even in the datasets which had different environmental and operational conditions than the training set, thus supporting the adaptability and the general applicability of the model across different infrastructural contexts.

4.3.3. Practical Application

The model was developed with practical application in mind above all else, being transparent and adaptable to everyday drinking water utility practice. There are various formats wherein it can be deployed, for example MATLAB or Python to run the fuzzy analysis, and then the results visualized in their GIS. While this is very straightforward, if not familiar, to many utility practitioners currently, resistance to its widespread and frequent use is inevitable. Adequate communication and strong support are key to achieving buy-in and marked results, with a phased approach having the highest likelihood of success. Focusing first on a tool to triage critical replacements or inspections would not only eliminate risk but also burgeon internal trust and valuable experience. This could even include using the tool to evaluate current plans and risk/financial prioritizations, providing clear, understandable results via benchmarking. As in all efforts of this nature, internal champions will also prove key to its success.

This model falls somewhere between legacy modeling efforts and the advanced, real-time AI decision support tools of the future, hence it's important for the users to realize its advanced nature without seeing it as a "black box". Its strengths, for example flexibility and handling uncertainty, should be well-explained in order to eliminate the notion that it comes perfectly tuned out of the box, but rather it's a valuable decision support tool to be married up to their current practices in an effective and clear way. This understanding builds trust in the process as well as promoting engagement in its further development and enhancement rather than resistance.

As small successes are realized through these early efforts, the model's use will grow and efforts will improve over time, to the point it finds its place, or an adaptation thereof, in the standard practices of all utilities nationwide in inspection planning, capital budgeting guidance. Paired with strong planning efforts and documentation thereof, the modeling efforts then demonstrate diligence and proactivity to governing bodies and other critical stakeholders, ratepayers included.

Ultimately these efforts can only benefit the industry when performed in an intelligent, responsible manner, eliminating risk, public mistrust, and budget shortfalls.

4.4. CONCLUSIONS

The findings of this research advanced infrastructure asset management by proposing a framework for financial optimization integrated with probabilistic deterioration modeling. The model developed is a significant departure from the traditional models that are either purely financial or based on heuristic failure rates. Instead, the framework adopted a hybrid soft-computing approach that incorporated pipeline deterioration dynamics, cost escalation, and probabilistic risk into a single decision support system.

Key contributions of this work include:

- Development of a Financially Embedded Fuzzy Renewal Model: The combination of financial metrics with predictive deterioration models is a newer contribution in the field of asset management decision making. The model ensures that intervention prioritization is capable of maintaining consistency with both degradation science and fiscal sustainability by incorporating cost re-weighting functions into a fuzzy inference system.
- Empirical Benchmarking Against Industry Heuristics: This research has also provided statistical evidence that the proposed framework can outperform existing break-rate replacement policies, Weibull-based hazard modeling, and static economic decision heuristics (e.g., EUAC). The results of the study support the conclusion that traditional heuristics are often inefficient in the use of capital, demonstrating that their results may be inadequate for the management of interventions in a financially limited planning process.
- Demonstration of Predictive and Economic Optimization Superiority: This research has proved that the approach is capable of enhancing both the predictive accuracy and economic efficiency of the renewal decision making process in the utility workshops. The model's capability to modify intervention suggestions according to the rate of degradation and availability of financial resources provides a more accurate guide for long-term capital allocation decisions.
- Advancement of Adaptive Analytics in Infrastructure Planning: This study also posited an important link between civil engineering, financial modelling and fuzzy inference systems by combining probabilistic degradation analysis with the cost of scheduling effective interventions. This contributes important data to the growing body of knowledge that calls for applying intelligent decision support systems in municipal asset management.

The collaborative utility workshops show that the use of heuristics based on break events leads to underinvestment in high-risk assets and imprecise allocation of renewal funds. The fuzzy degradation inference engine addresses these inefficiencies by incorporating a richer set of predictive factors into the decision-making process, thus offering a decision support system that is more reflective of actual degradation trends as opposed to failure concentrations. Furthermore, the results of this study can be directly applied to policy making at the municipal, state, and federal levels. The research suggested a real need for policies that support rational renewal scheduling approaches, especially for utilities applying for state or federal infrastructure investment funds. Formal incorporation of financial optimization and predictive modelling into the regulatory frameworks helps ensure that infrastructure renewal budget allocations are made in the very best way. This acknowledged, the analysis provided reveals that the utility of probabilistic degradation modeling within the context of optimal replacement timing is comparative to existing effective methodologies. This paper has also established that the application of fuzzy logic for probabilistic degradation modeling and financial optimization is computationally efficient and empirically valid. One of the primary constraints to this is the current limited availability and detail of utility data, particularly for historical failure records, remaining wall thickness measurements, and soil corrosivity indices. Despite being developed to work in conditions of data scarcity with the help of robust inference mechanisms, the model's predictive accuracy and financial optimization capacity could be improved with the inclusion of high-frequency, real-time pipeline monitoring data. While the present approach is capable of integrating financial optimization with the probabilistic degradation modeling, it is worthwhile to investigate the feasibility of incorporating advanced machine learning techniques like deep reinforcement learning for tuning of the intervention time based on the dynamic pipeline performance measurements. The integration of self-learning optimization components in the decision framework would increase the framework's adaptability and robustness when applied to extended planning horizons. An alternative direction for future study can be found in the creation of a real-time GIS integrated decision support system in the form of a dashboard which would enable utility managers to visualize the pipeline degradation paths, recommended times for intervention, and financial optimization scenarios spatially. Not only would such an implementation improve decision making transparency, it would also facilitate the realization of computationally driven renewal prioritization methodologies for real world infrastructure planning. While the current study leverages fuzzy logic for predictive modeling, future research could explore the potential for deep reinforcement learning to enhance intervention timing optimization. The application of self-learning AI methodologies could further refine renewal prioritization, allowing the model to dynamically adapt to evolving infrastructure performance datasets.

5. CONCLUSION AND RECOMMENDATIONS FOR FUTURE WORK

5.1. SUMMARY OF RESEARCH

This dissertation explores the value of using better data to enhance current performance modeling efforts as a framework to maximize the success of water main asset management. With quality data and validated modeling techniques utility managers can ably lower failure risk while concurrently stretching budgets to acceptable levels. Where prior models focused on only a few drivers in a static manner, this research leveraged a high-quality dataset along with hard-coded industry best practices to develop and implement a Type-2 fuzzy logic model with remarkable success at guiding water main renewal intervention type and timing according to established best practices, even in instances where data was missing or not empirical. The model was capable of navigating uncertainty while resourcing physical, economic, and spatial metrics to ably manage water main assets across diverse regions in the U.S.

The research timeline began with analyzing industry triple bottom line cost data to identify best and moreover missing practices essential for advanced, valuable modeling efforts. Various modeling techniques were explored and tested with the data but the focus was on those of a financial nature, namely the EUAC and LCC methods of determining the best management strategy for various pipes based on techniques borrowed from the financial world. As the success of these models fell short of acceptable levels the research took a path into soft-computing methods to overcome the inherent limitations in deterministic modeling. The fuzzy model was calibrated using 37,000 break and remaining wall thickness records and then tested with utilities in live situations, on problematic areas where the managers sought to compare it their own in-house standard practices as well as some more advanced AI-modeling results provided via professional consultants. The model's success was finally gauged in a blind test where it showed an accuracy of 85% in choosing the best renewal method and timing as defined by established industry standards (AWWA M28/77).

5.2. PRINCIPAL CONTRIBUTIONS

This research makes several important contributions to the study of buried water main asset management, including:

- Water main renewal project financial data standard: industry data was collected and analyzed in a novel and advanced way which provided a solid foundation for analyzing cost trends, best industry practices in managing budgets, and testing/developing models and tools for successful planning and management
- Financial Model Evaluation: EUAC and LCC models were tested and benchmarked for their abilities to provide robust decision support in the proper project type selection and timing using financial metrics such as annualized and holistic life cycle costs. These efforts showed that deterministic financial modeling alone was not quite adequate in providing acceptable standalone support, yet the insights provided valuable guidance in developing a more advanced model incorporating both physical and economic performance metrics into a spatially-aware, adaptable soft computing framework able to handle the uncertain and complex niche of buried pipe behavior modeling via fuzzy membership function design.
- Type-2 Fuzzy Logic-based Economic Model for Water Main Renewal Decision-Support: The fuzzy inference model was developed based on the industry knowledge and revelations of the research using Gaussian smoothing and Type-2 membership functions to not only perform in common situations but to also handle edge cases appropriately. The model employs key parameters such as location, pipe environment, and financial health to make accurate and timely decisions due to its calibration using 37,000 pipe records from various utilities spread across the U.S. These efforts drove the model to achieve an average of 85% accuracy in utility workshops, including a blind test on pipe data with robust ground truth data where the best management strategy for each node was clear.

5.3. PRACTICAL IMPLICATIONS

The developed methodology provides utility practitioners with a set of tools grounded in industry's best heuristics to ably tackle situations not ideal for successful pipe performance modeling and moreover long-term O&M and capital planning. This will help them:

- Mitigate catastrophic failure risk thereby protecting the public & environment
- Avoid the misallocation of funds in improper renewal intervention type selection and timing
- Drive continued improvement in water main asset management through further collaboration, and moreover lack of emergency events causing major burdens on resources

The nature of the model is adaptable to linear infrastructure and hence could provide marked value to the wastewater, transportation, and energy industries.

5.4. LIMITATIONS AND FUTURE WORK

Although the research was successful in developing a robust framework and validated fuzzy logic tool for buried water main renewal intervention prioritization, many limitations linger. For instance, the calibration was completed on a large verified dataset directly from the utilities and federal government, but information quality and adequacy can always improve. Further, the research focused on larger metallic water mains and needs to include PVC and concrete pipes as well to be a staple tool for utilities. Moreover, as most utilities are not using MATLAB, the conversion of the model code into Python (currently ongoing) is key to its widespread use in the industry. The next steps in this research path would include:

- Real-time sensory-driven GIS integration on a cloud-based platform
- further validation on larger and better datasets
- enhancement via the latest AI tools
- integration with Monte Carlo-driven deterioration modeling to support better risk/cost decision support to greatly refine long term water system planning.

A study in the near future to evaluate outcomes of decisions made using the framework and its apparent usefulness to utility managers in identifying poor pipe performance and the respective best investment strategies would be very insightful.

As investments into advanced decision support systems for water main infrastructure space grow, the value of the understanding and adoption of these tools will be increasingly advantageous for water utility asset managers and those managing similar critical asset systems. Those tasked with the engineering and policy-making need the support of these frameworks for their ability to ably communicate the risks inherent in their systems which leads to less downtime and potential harm to the public/ environment, and transparent, defensible decision making. As the successful management of water infrastructure systems critical to sustaining life become less and less troublesome it then frees up resources and fundamentally improves human life.

6. REFERENCES

Allbee, S. (2005). "America's pathway to sustainable water and wastewater systems." Water Asset Management International, 1(1), 9-14

American Water Works Association (AWWA). Manual M28: Rehabilitation of Water Mains. 3rd ed. Denver, CO: American Water Works Association, 2014.

American Society of Civil Engineers (ASCE). 2021 Report Card for America's Infrastructure. ASCE, 2021. www.infrastructurereportcard.org

AWWA. (2017). Buried No Longer: Confronting America's Water Infrastructure Challenge. American Water Works Association.

AWWA. (2021). 2021 State of the Water Industry Report. American Water Works Association.

AWWA. Buried No Longer: Confronting America’s Water Infrastructure Challenge. AWWA Report, 2012.

Baird, G.M. Collection System O&M Best Practices: A Guide for the Wastewater Collection System Operator. Water Environment Federation, 2011.

Butler, D., & Davies, J. W. (2011). Urban Drainage (3rd ed.). CRC Press.

Carson, C., & Culp, C. (2002). Use of condition assessment tools in large pipeline decision making. Proc. ASCE Pipeline Conference.

Clark, R. M., Sivaganesan, M., Selvakumar, A., and Sethi, V. (2002). "Cost models for water supply distribution systems." Journal of Water Resources Planning and Management, 128(5), 312-321

Cloutier, V., et al. "A Review of Performance Indicators for Strategic Asset Management of Drinking Water Infrastructure." Water Research, 173, 2020: 115556.

Coghill, M. R., Faber, N. D., Corrao, A., and Garrett, C. (2018). “Condition assessment of concrete bar-wrapped cylinder pipe, the next phase of San Diego County Water Authority’s asset management program.” Pipelines 2018: Condition Assessment, Construction, and Rehabilitation, Reston, VA: American Society of Civil Engineers.

Dandy, G.C., et al. "Optimal Scheduling of Water Pipe Renewal Using Genetic Algorithms." Journal of Water Resources Planning and Management, 133(2), 2007: 135–143.

Deb, K. (2001). Multi-objective Optimization Using Evolutionary Algorithms. John Wiley & Sons.

Deb, K., & Gupta, H. (2005). Searching for robust Pareto-optimal solutions in multi-objective optimization. Evolutionary Multi-Criterion Optimization.

Farmani, R., Walters, G.A., & Savic, D.A. "Evolutionary Multi-Objective Optimization in Water Distribution Network Design." Engineering Optimization, 37(2), 2005: 167–183.

Ge, S., Xu, H., & Sinha, S. K. (2017). Validation of infrastructure deterioration models using national break and RWT data. Journal of Pipeline Systems Engineering and Practice, 8(4), 04017015.

Gilchrist, A. (2005). Societal cost estimation framework for trenchless and open-cut pipeline technologies. North American Society for Trenchless Technology.

Goddard, J., & Hanke, A. (2020). Lifecycle cost models for sustainable water asset planning. Water Research Foundation Report #4726.

Halfawy, M. "Integrated Decision Support System for Optimal Asset Renewal Planning." Journal of Computing in Civil Engineering, 22(5), 2008: 320–329.

Herz, R. K. (1999). Rehabilitation of water mains: planning and implementation. AWWA Research Foundation.

ISO 55000. Asset Management – Overview, Principles, and Terminology. International Organization for Standardization, 2014.

Jung, D., & Sinha, S.K. "Quantification of Social Costs Associated with Trenchless Technologies." Purdue University, Center for Underground Infrastructure Research and Education (CUIRE), 2007.

Kang, D., Lansey, K., & Gabriel, S. A. (2008). Inexact multi-objective programming model for water infrastructure rehabilitation. Computer-Aided Civil and Infrastructure Engineering, 23(8), 604–619.

Kang, D., Lansey, K., & Yang, S.L. "Decision Support System for Optimal Scheduling of Water Main Rehabilitation." Journal of Water Resources Planning and Management, 136(5), 2010: 519–527.

Kleiner, Y., & Rajani, B. "Comprehensive Review of Structural Deterioration of Buried Pipes." Urban Water Journal, 4(3), 2007: 185–196.

Kleiner, Y., & Rajani, B. (2001). Comprehensive review of structural deterioration of buried pipelines. Urban Water, 3(3), 131–150.

Kleiner, Y., & Rajani, B. (2010). Practitioner's approach to condition assessment of drinking water pipelines. Journal of Water Supply: Research and Technology—AQUA, 59(5), 327–336.

Kleiner, Y., Rajani, B., & Sadiq, R. (2010) "Modelling the Deterioration and Repair of Water Infrastructure." Canadian Journal of Civil Engineering, 37(6), 2010: 849–860.

Koduru, S., & Baran, G. "Neural Network Based Condition Assessment of Pipelines." Automation in Construction, 13(5), 2004: 737–745.

Koo, D., Piratla, K.R., & Matthews, C.J. "Towards Sustainable Water Supply: Schematic Framework for Life-Cycle Cost Analysis." Sustainable Cities and Society, 10, 2014: 69–76.

Lemer, A.C. "Progress Toward Integrated Infrastructure-Asset-Management Systems." Journal of Infrastructure Systems, 3(1), 1997: 1–16.

Loubier, J., et al. (2021). Optimizing water main replacement using break history and socioeconomic risk. Water Research, 191.

Loucks, D.P., & van Beek, E. Water Resources Systems Planning and Management: An Introduction to Methods, Models and Applications. UNESCO, 2005.

MacLeod, I.D., & Sinha, S.K. "Best Practices in Condition Assessment of Buried Water Mains." U.S. EPA Report, 2009.

Marlow, D. R., Beale, D. J., & Burn, S. (2010). A review of diagnostic techniques to predict pipe condition. Water Research, 44(5), 1355–1366.

Moglia, M., & Maheepala, S. "Evaluating Water Supply Infrastructure Performance." Urban Water, 1(1), 1999: 21–33.

Moglia, M., Burn, S., & Meddings, D. "Decision Support for Strategic Asset Management of Water and Wastewater Infrastructure." Water Science and Technology, 58(3), 2008: 425–434.

Moglia, M., et al. (2006). Decision support systems for water pipeline renewal planning. Journal of Water Supply: Research and Technology—AQUA, 55(6), 393–407.

Mohammadi, S., & Vanier, D.J. "Framework for Performance Assessment of Municipal Infrastructure Using Fuzzy Logic." Journal of Performance of Constructed Facilities, 22(5), 2008: 285–292.

Najafi, M., & Gokhale, S. "Trenchless Technology for Installation of Cables and Pipelines." Journal of Construction Engineering and Management, 131(7), 2005: 743–752.

Najafi, M., & Gokhale, S. "Trenchless Technology: Pipeline Renewal Options." Practice Periodical of Hazardous, Toxic, and Radioactive Waste Management, 19(2), 2015: 52–60.

Najafi, M., & Kulandaivel, G. (2005). Life-cycle cost comparison of trenchless and conventional open-cut construction methods. Tunnelling and Underground Space Technology, 20(2), 123–132.

NIBS. (2003). Life Cycle Costing Manual for the Federal Energy Management Program. National Institute of Building Sciences.

Rajani, B., & Kleiner, Y. "Non-Destructive Inspection Techniques to Determine Structural Distress Indicators in Water Mains." National Research Council of Canada, 2001.

Rajani, B., & Kleiner, Y. (2001). Comprehensive review of structural deterioration of water mains. National Research Council of Canada.

Romero, D., & Ruiz, M.C. "A Review of Recovery Strategies for Asset Failures in Urban Water Systems." Water Research, 158, 2019: 298–311.

Ross, T. J. (2004). Fuzzy Logic with Engineering Applications (2nd ed.). Wiley.

Ross, T.J. Fuzzy Logic with Engineering Applications. 2nd ed. Wiley, 2004.

Saaty, T. L. (1980). The Analytic Hierarchy Process. McGraw-Hill.

Saaty, T.L. Decision Making with the Analytic Hierarchy Process. Springer, 2008.

Sadiq, R., & Kleiner, Y. "Risk-Based Decision Making for Sustainable Municipal Infrastructure." Canadian Journal of Civil Engineering, 33(12), 2006: 1457–1470.

Sadiq, R., et al. (2004). Fuzzy-based reliability model for water distribution systems. Journal of Water Resources Planning and Management, 130(6), 405–414.

Shamir, U., & Howard, C. D. D. (1979). An analytical approach to scheduling pipe replacement. Journal of the American Water Works Association, 71(5), 248–258.

Sinha, S.K., & Knight, M.A. "Intelligent Decision Support System for Sewer Infrastructure Rehabilitation and Replacement." Journal of Computing in Civil Engineering, 18(3), 2004: 276–284.

Sinha, S.K., & Sadiq, R. "Probabilistic Risk Analysis for Sewer System Infrastructure." Journal of Construction Engineering and Management, 133(8), 2007: 947–960.

St. Clair, A. M., Sinha, S. K., & Baird, G. (2015). *Standardized cost and condition assessment frameworks: Lessons from the WATERiD initiative.* Virginia Tech SWIM Lab technical report.

Stratton, L., et al. (2020). Integrated spatial risk modeling of water mains using GIS and failure prediction algorithms. Journal of Infrastructure Systems, 26(1).

Taiwo, R., Ben Seghier, M. E. A., and Zayed, T. (2023). "Toward sustainable water infrastructure: The state-of-the-art for modeling the failure probability of water pipes." *Water Resources Research*, 59(3), e2022WR033256.

Vairavamoorthy, K., Eckart, J., Tsegaye, S., & Ghebremichael, K. "Integrated Urban Water Management." Urban Water Journal, 5(4), 2008: 307–314.

Vanier, D.J. "Asset Management 101: A Primer for Facility Managers." National Research Council Canada, 2000.

Vishwakarma, A. (2019). Development of a performance analysis framework for water pipeline infrastructure using systems understanding (M.S. thesis). Virginia Polytechnic Institute and State University.

Walski, T.M., et al. Advanced Water Distribution Modeling and Management. Haestad Press, 2003.

Water Finance & Management. (2024). Maximizing condition assessment. Retrieved July 16, 2025, from https://waterfm.com/maximizing-condition-assessment/

Wirahadikusumah, R., Abraham, D.M., & Iseley, T. "Assessment Technologies for Sewer System Rehabilitation." Automation in Construction, 10(4), 2001: 471–479.

Xu, B., & Sinha, S.K. "Empirical Models for Estimating Pipe Breaks in Water Distribution Systems." Journal of Water Resources Planning and Management, 145(9), 2019: 04019035.

Xu, C. (2022). Empirical evaluation of pipe deterioration and replacement prioritization. Journal of Pipeline Systems Engineering and Practice.

Xu, C., & Sinha, S. K. (2019). Predictive models for water pipeline failures using survival analysis. Journal of Infrastructure Systems, 25(3).

Zadeh, L. A. (1965). Fuzzy sets. Information and Control, 8(3), 338–353.

Zadeh, L.A. "Fuzzy Logic = Computing with Words." IEEE Transactions on Fuzzy Systems, 4(2), 1996: 103–111.

Zadeh, L.A. "Fuzzy Sets." Information and Control, 8(3), 1965: 338–353.

A. APPENDIX A SUPPLEMENTARY TABLES AND FIGURES

Table A1. CA Tools from USEPA Study

Technology	Cost ((10,000-ft) ($/ft))		
Leak Detection/Wall Thickness	Leak Detection	Wall Thickness	Both
Echologics LeakFinderRT	2	N/A	2.7
Pure SmartBall™	4.5	6	8.5
PPIC Sahara ® Leak Detection	2.2	3.3	4.4
Average Wall Thickness over X Length			
PPIC Sahara® Pipe Wall Thickness Assessment	N/A	3.3	4.4
Pure SmartBall™ Pipe Wall Assessment (PWA)	N/A	6	8.5
Echologics Thickness Finder	N/A	N/A	2.7
Internal Inspection	Total Cost for 10,000 ft ($)		
PPIC Sahara® Video	29,000		
PPIC PipeDiver ®	N/A		
Russell SeeSnake®	156,000 - 196,000		
External Inspection			
RSG – Broadband Electromagnetic (BEM) Hand Scanning Kit (HSK)	N/A		
Crown Assessment Probe (CAP)	N/A		
AESL – Magnetic Flux Leakage (MFL), soil characteristics, UT, FEA	N/A		

Table A2. Actual and Estimated Costs for Assessment and Restoration Work

Item	**Cost**
Basic Condition Assessment: 3831 feet @ $18 (15% of $120)	$68,958
Report Including Asset Management and Prescription for Restoration with Performance Guarantee: 3831 feet @ $6 (5% of $120)	$22,986
Year 1 Prescription: 10 clamps installed @ $2000	$20,000
Year 1 Prescription: 5 segments replaced @ $3300	$16,500
Year 1 Prescription: 31 anodes installed @ $350	$10,850
Year 5 Prescription: 26 anodes installed @350, present value, discounting at 4%	$7,780
Total Cost of Assessment, Restoration, and Guarantee	$147,074
Cost of Full Replacement: 3831 feet @ $120	$459,720

Table A3. Rehabilitation Alternatives for 66-Inch Water Main

Technology	**Description**	**Service Life**	**Cost**
Insituform CIPP Pressure Pipe Liner	A sliplined epoxy impregnated liner that becomes an integrated component of the pipe. Requires refrigerated truck and onsite water for liner inversion, and steam or water heating equipment	50+ years	Anticipated to be $40,000 for pipe section removal for liner insertion. Liner cost is unknown.
Epoxy	Ultra-high solids epoxy. Spray applied, high build, with edge retentive qualities. Requires heated spray system, truck-mounted air compressor.	8–12 years	$175,000–$200,000 including removal and disposal of existing lining
Polyurea	100% solids, spray applied lining system, with greater flexibility, adhesion	20+ years	10%–30% greater cost than epoxy

	and abrasion characteristics than epoxy. Requires heated spray system, truck-mounted air compressor.		
Polyurethane	100% solids, spray applied lining system with greater flexibility, adhesion and abrasion characteristics than epoxy. Requires heated spray system, truck-mounted air compressor.	15+ years	10%– 30% greater cost than epoxy
Raven Lining System	100% solids, spray applied epoxy that can be applied to dry or damp surfaces. Requires heated spray system, truck-mounted air compressor.	20+ years	$175,000–$200,000 including removal and disposal of existing lining

Table A4. Cost Data Standard

Description of Data	Desired Data
Region	USEPA Regions 1-10
Utility	Utility
Project Name	Project Name/Phase
Project Location Zip	Location
Bid Date	Date work bid, MM/DD/YYYY
Work Start Date	Date work started, MM/DD/YYYY
Work End Date	Date work ended, MM/DD/YYYY
Item Duration	Hours
(LF/HR)	Production
Project Type	Condition Assessment (CA) or Renewal Engineering (RE)
Application Type	Continuous or Point Repair
Existing Pipeline Type	In-situ Pipeline Material
Existing Pipeline Size	Inner Diameter (inches)
New Pipeline Type	New Pipeline Material
New Pipeline Size	Inner Diameter (inches)
Pipeline Rating Class	Pressure Classification
Rating	Rating in PSI, Size-dimension ratio, Thickness (in, mm, etc.)

Depth	Depth
Age	Pipe Age
Technology Used	Type of Work (CIPP, Pipe Bursting, etc.)
Scope of Work	Continuous or Point Repair
Units	(Lineal Feet, Each, Hours, etc.)
Cost per Unit	Dollars
Item Total	Bid Item Total
Total Cost	Total Contract
Item Percent of Total	Percent
Planning, Design, or Training Costs: Description and Percentage of Total	Costs
Mobilization	Costs
Traffic Control	Costs
Temporary Main	Costs
Main Reconnection	Costs
Service Reconnection	Costs
Valves, Fittings, Cathodic Protection, Hydrants, etc.	Costs
Earthwork	Costs
Testing/Inspection	Costs
Surface Restoration Costs:	Costs
Safety Costs (Shoring, etc.)	Costs
Runoff/SWPPP	Costs
Abandonment/Disposal Costs	Costs
Change Orders	Costs
Additional Costs due to Crossings: Description and cost	Costs
Traffic Disruption	Costs
Lost Revenue for Adjacent Businesses	Costs
Noise Pollution	Costs
Funding Source	(Internal Funds, Bonds, Grants, etc.)
Cost of Capital	% of Total Cost
Total Cost all inclusive	Total Cost
On Budget	(Yes/No)
On Schedule	(Yes/No)
Drivers	Primary Drivers for Project (Increased demand, Failure, New funding, etc.)
Circumstances	(Routine/Challenging/Difficult/Emergency)
Notes	Please provide guidance as to what made these costs differ from typical
Other Notes	Text
File path or web address	Information Link

Table A5. Parameter Data Quality and Weighting in Fuzzy Inference

Parameter	Category	Weighting (0-1)
Pipe Age	Structural Integrity	1
Pipe Material	Structural Integrity	0.95
Pipe Break	Structural Integrity	1
C Factor	Structural Integrity	0.7
Remaining Wall Thickness	Structural Integrity	1
Water Quality	Internal Condition	0.7
Water Temperature	Internal Condition	0.8
Pressure	Internal Condition	0.9
Adequate Fire Flow	Internal Condition	0.6
Customer Complaints	Internal Condition	0.5
Lining Type	Internal Condition	0.7
Flooding Frequency	External Stress	0.6
Drainage Class	External Stress	0.7
Particle Size	External Stress	0.6
Buried Depth	External Stress	0.8
Subsurface Temperature	External Stress	0.6
Traffic Loading	External Stress	0.75
Water Table Depth	External Corrosion	0.7
Groundwater Fluctuation	External Corrosion	0.6
Soil Corrosivity	External Corrosion	0.9

Cathodic Protection	External Corrosion	0.5
Stray Currents	External Corrosion	0.4
Coating Type	External Corrosion	0.7
Asset Replacement Cost	Economic Performance	0.85
Unrecovered Water Loss	Economic Performance	0.75
Litigation and Regulatory Costs	Economic Performance	0.5
Collateral Damage Cost	Economic Performance	0.65
Compliance Violation Costs	Economic Performance	0.55
Site Restoration Cost	Economic Performance	0.65
Customer Impact Cost	Economic Performance	0.75
Traffic Management Costs	Economic Performance	0.85
Water Service Quality Penalty	Economic Performance	0.6
O&M Budget Impact	Economic Performance	0.65
Emergency Flow Capacity Cost	Economic Performance	0.5
Pressure-Related Maintenance Cost	Economic Performance	0.65
System Redundancy Factor	Economic Performance	0.75
Site Preparation Costs	Economic Performance	0.7
Pipe Excavation Difficulty	Economic Performance	0.8
Pipe Depth Installation Cost	Economic Performance	0.8
Information Gaps	Economic Performance	0.55
Spare Parts Availability	Economic Performance	0.65

Table A6 Comparison of Type 1 & 2 Fuzzy Models

Feature	Type 1 Fuzzy Model	Type 2 Fuzzy Model
Membership Function Type	Single-valued	Footprint of uncertainty
Handling of Uncertainty	Low	High
Model Flexibility	Moderate	High
Interpretability	High	Moderate
Data Requirements	Low	Moderate
Adaptability	Good	Excellent
Use Case Suitability	Well-defined systems	Complex systems
Real-world Performance	Good	Superior

Table A7. Top 15 Most Sensitive Inputs Affecting LCC

Input Parameter	Std Dev of LCC
Traffic Loading	31000
Pipe Material	29500
Compliance Violation Costs	27000
Pipe Depth Installation Cost	26000
Site Preparation Costs	25000
Spare Parts Availability Impact	24000
Customer Impact Cost	23000
Information Gaps (Documentation Cost)	22500
System Redundancy Factor	22000
Traffic Management Costs	21500
Water Service Quality Penalty	21000
Collateral Damage Cost	20500
Asset Replacement Cost	20000
Unrecovered Water Loss	19500
Litigation and Regulatory Costs	19000

Table A8. Sensitivity of Risk Score in Input Variation

Input Parameter	Std Dev of Risk Score
Traffic Loading	3.1
Pipe Material	3
O&M Budget Impact (Overruns)	2.9
Water Service Quality Penalty	2.8
Traffic Management Costs	2.7
Road/Rail Traffic Disruption Cost	2.6
Information Gaps (Documentation Cost)	2.5
Cost of Property Damage	2.4
System Redundancy Factor	2.3
Customer Impact Cost	2.2
Pipe Depth Installation Cost	2.1
Asset Replacement Cost	2
Compliance Violation Costs	1.9
Pipe Break	1.8
Unrecovered Water Loss	1.7
Litigation and Regulatory Costs	1.6
Collateral Damage Cost	1.5
Particle Size	1.4
Stray Currents	1.3
Remaining Wall Thickness	1.2
Adequate Fire Flow	1.1
Lining Type	1
Groundwater Fluctuation	0.9
Flooding Frequency	0.8
Drainage Class	0.75
Customer Complaints	0.7
Coating Type	0.65
Cathodic Protection	0.6
Subsurface Temperature	0.55
Water Temperature	0.5
Water Table Depth	0.45
Buried Depth	0.4
Water Quality	0.35
C Factor	0.3
Spare Parts Availability Impact	0.25
Pressure-Related Maintenance Cost	0.2
Pipe Age	0.15
Emergency Flow Capacity Cost	0.1
Pressure	0.05
Site Preparation Costs	0.02

Soil Corrosivity	0.01

Table A9. Error in Model Choices with Best Practice

Model	Accuracy	Recall	F1 Score	RMSD	NMAE
Fuzzy Model (Type 2)	0.87	0.83	0.85	0.13 +/- 0.02	0.11 +/- 0.01
EUAC Heuristic	0.68	0.65	0.66	0.19	0.17
Break-Rate Heuristic	0.61	0.58	0.59	0.21	0.18

Table A10. Blind Testing Results

Feedback Category	**Summary of Comments**
Alignment with Ground Truth	Over 85% of model results matched ground truth data
Discrepancies Identified	Remaining 15% of outputs had lesser data to compare to hence were not wrong necessarily
Assessment of Model Utility	Suitable for utility use
Overall Conclusion	Model performs on par with those in practice

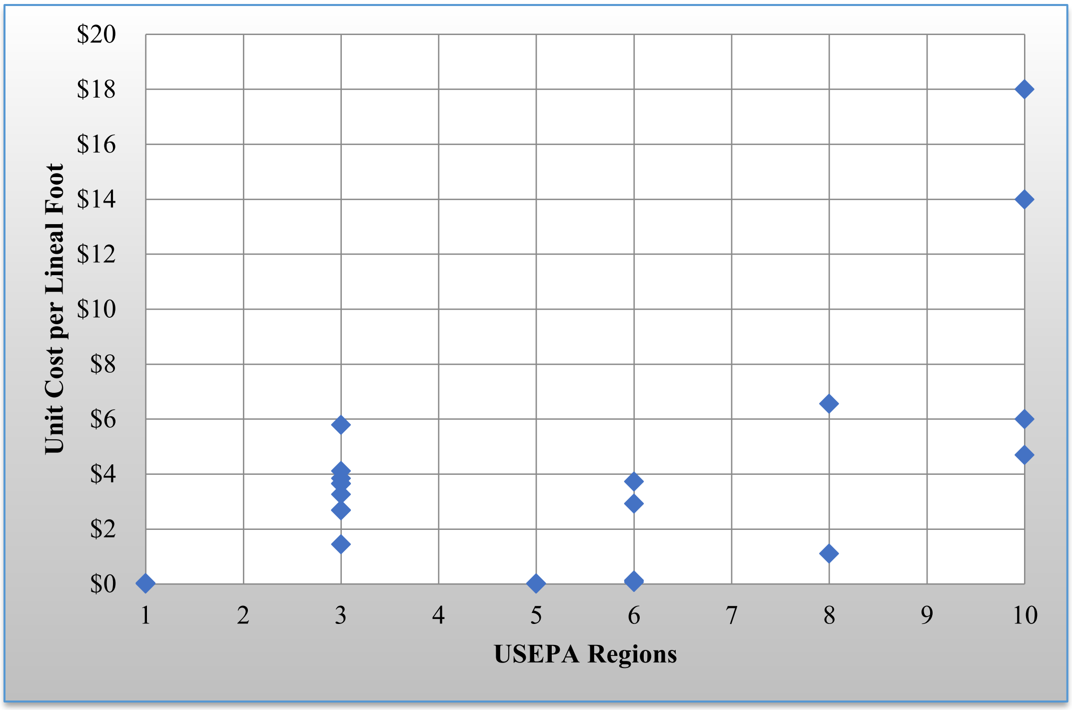

Figure A1. Unit Cost of Leak Detection by USEPA Region

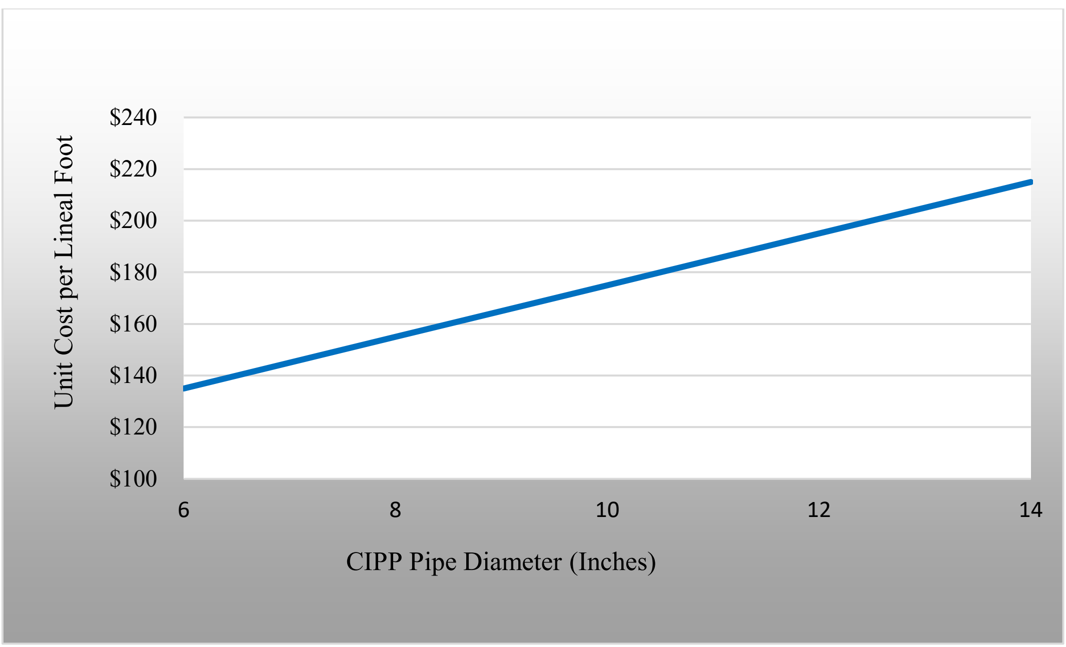

Figure A2. CIPP Unit Cost by Diameter

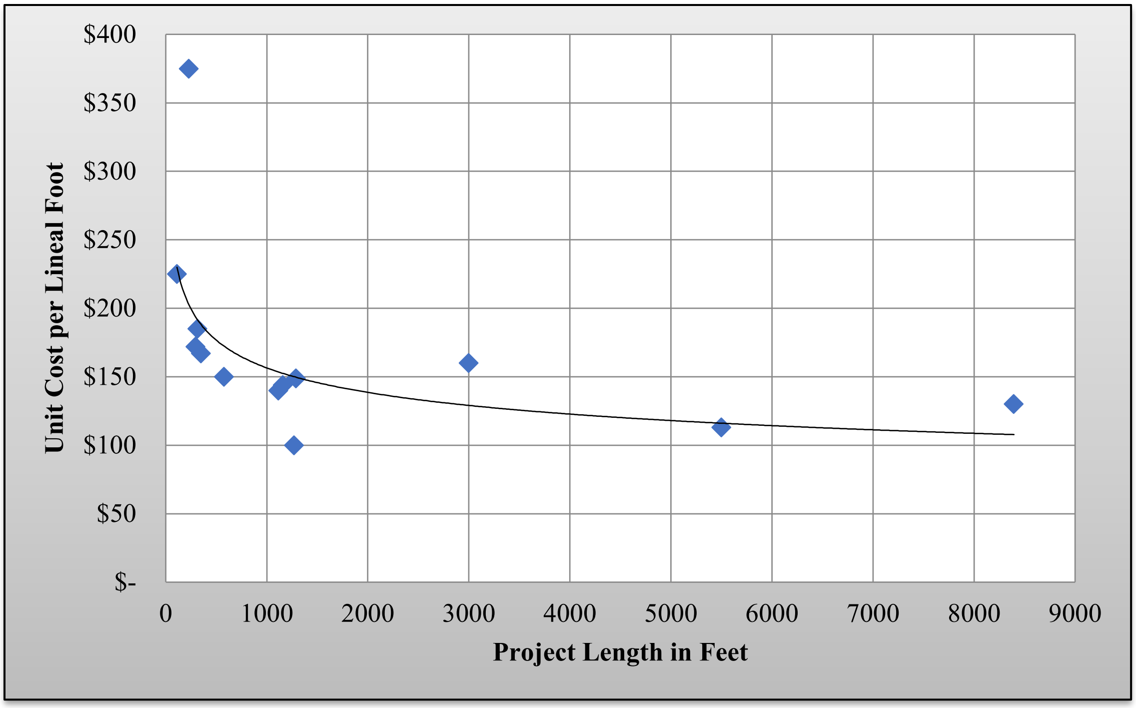

Figure A3. CIPP Unit Cost by Project Length

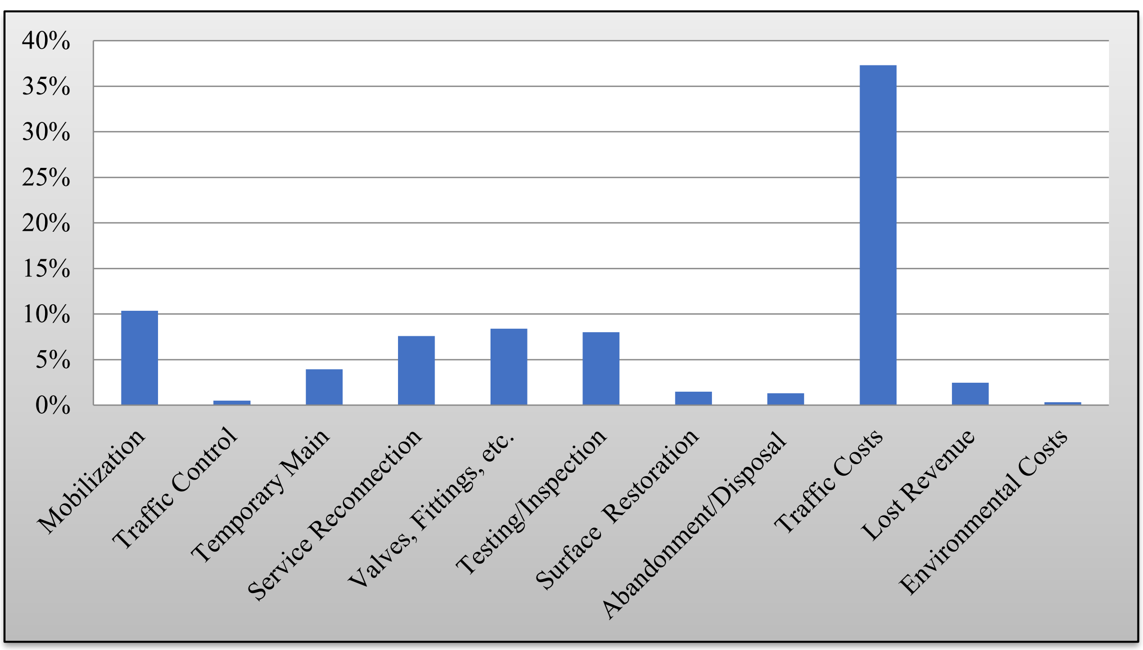

Figure A4. Supplemental Costs of CIPP Work by Percentage of Cost Burden

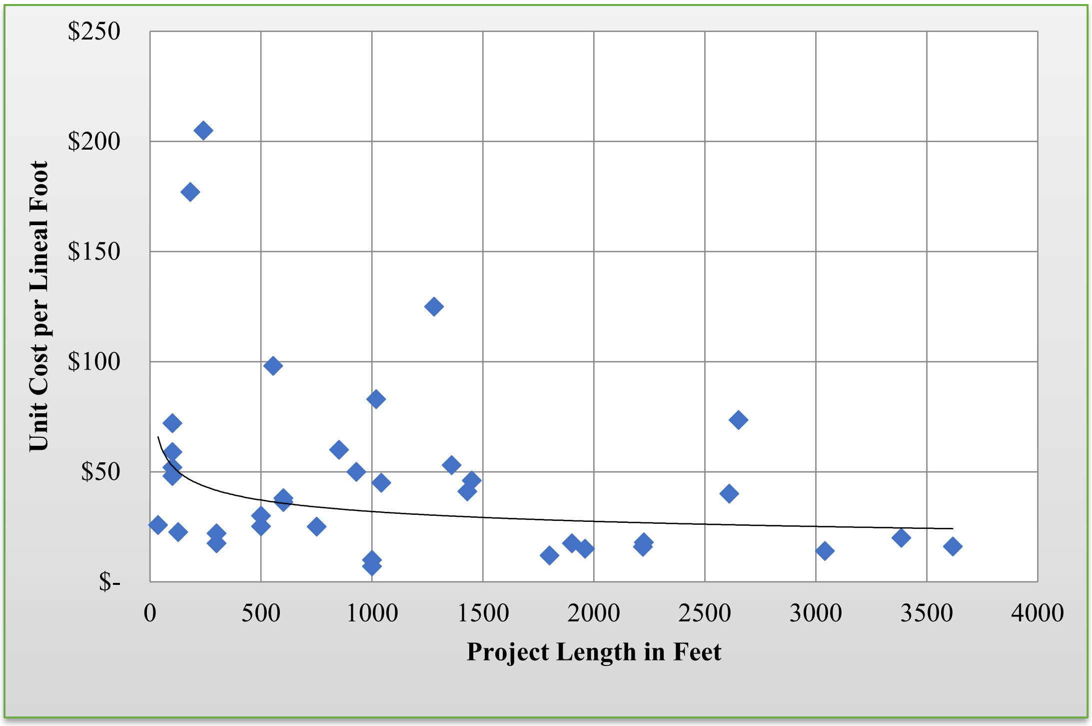

Figure A5. HDD Unit Costs by Length

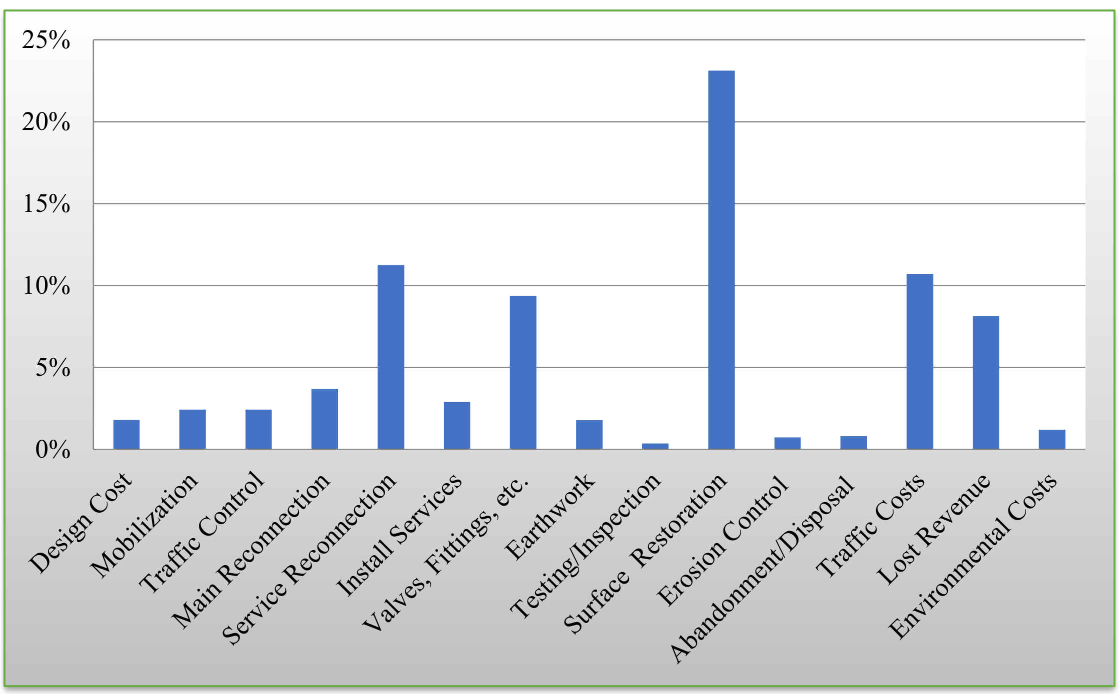

Figure A6. Supplemental Costs of HDD Work by Percentage of Cost Burden

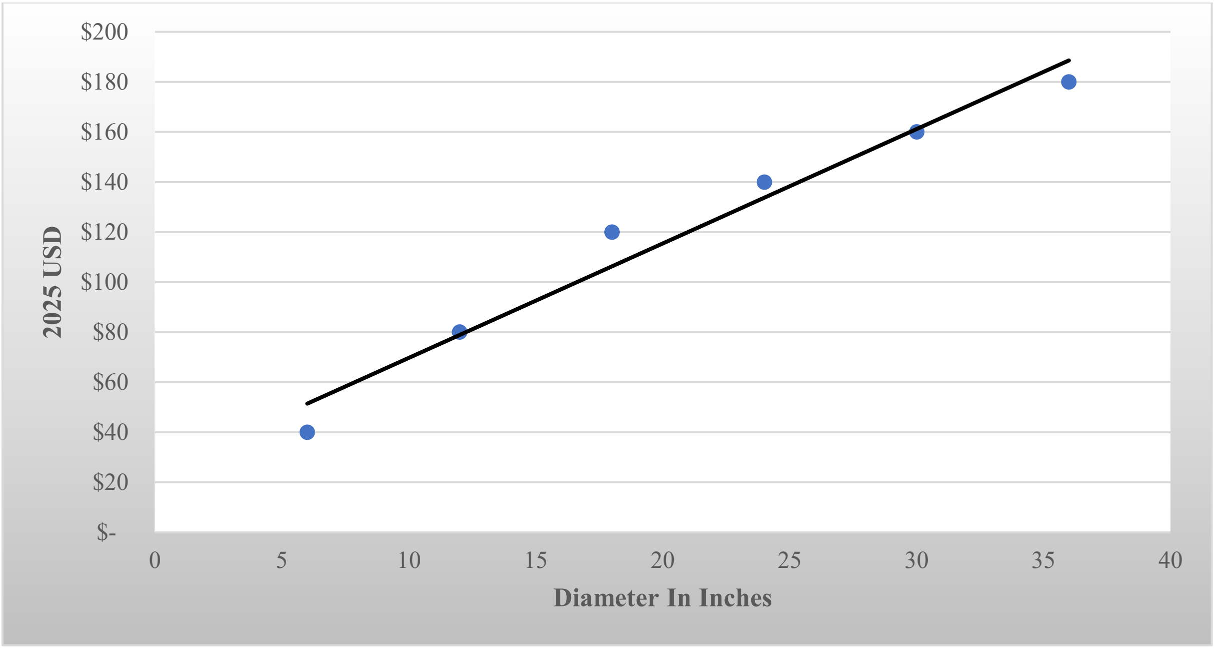

Figure A7. Open Cut Unit Cost by Diameter

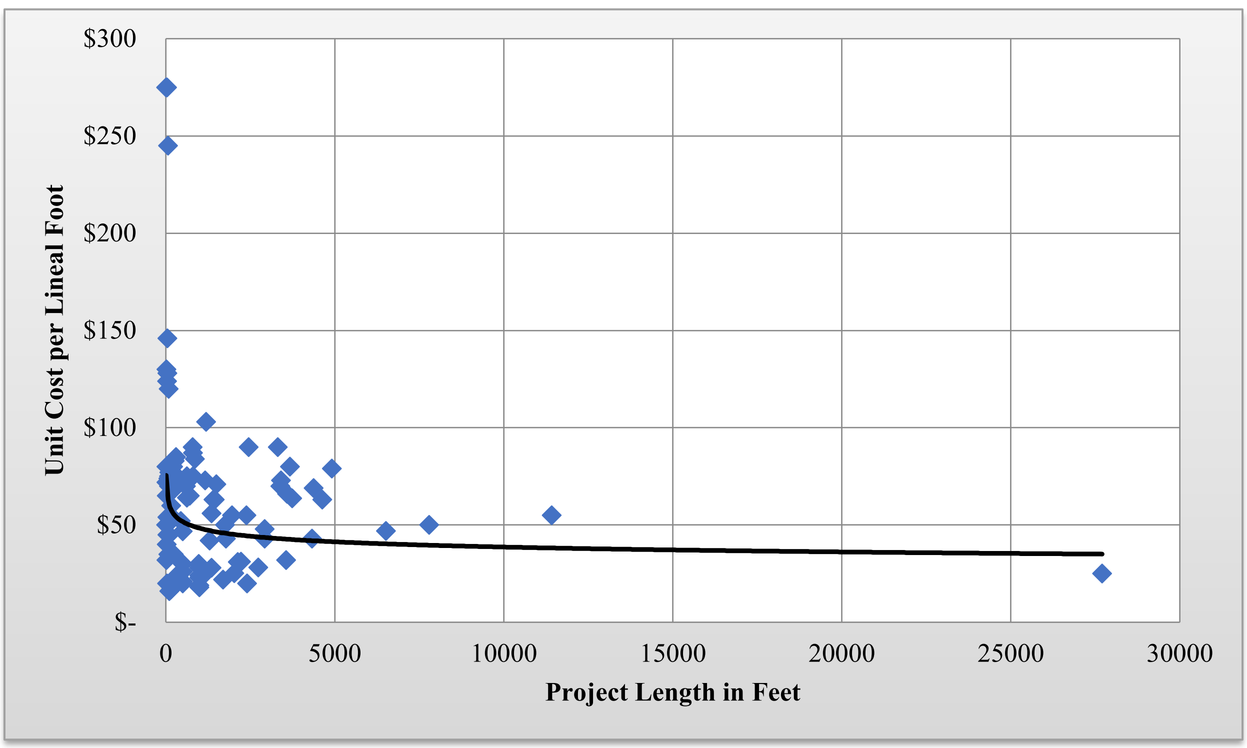

Figure A8. Open Cut Unit Costs by Length

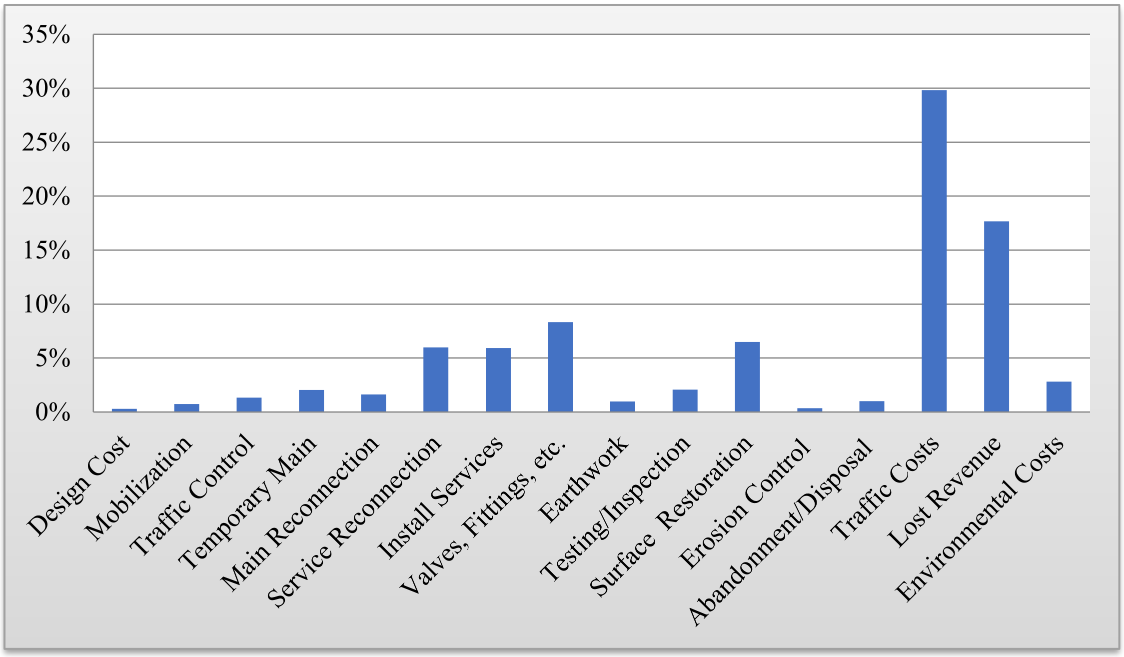

Figure A9. Supplemental Costs of Open Cut Work by Percentage of Cost Burden

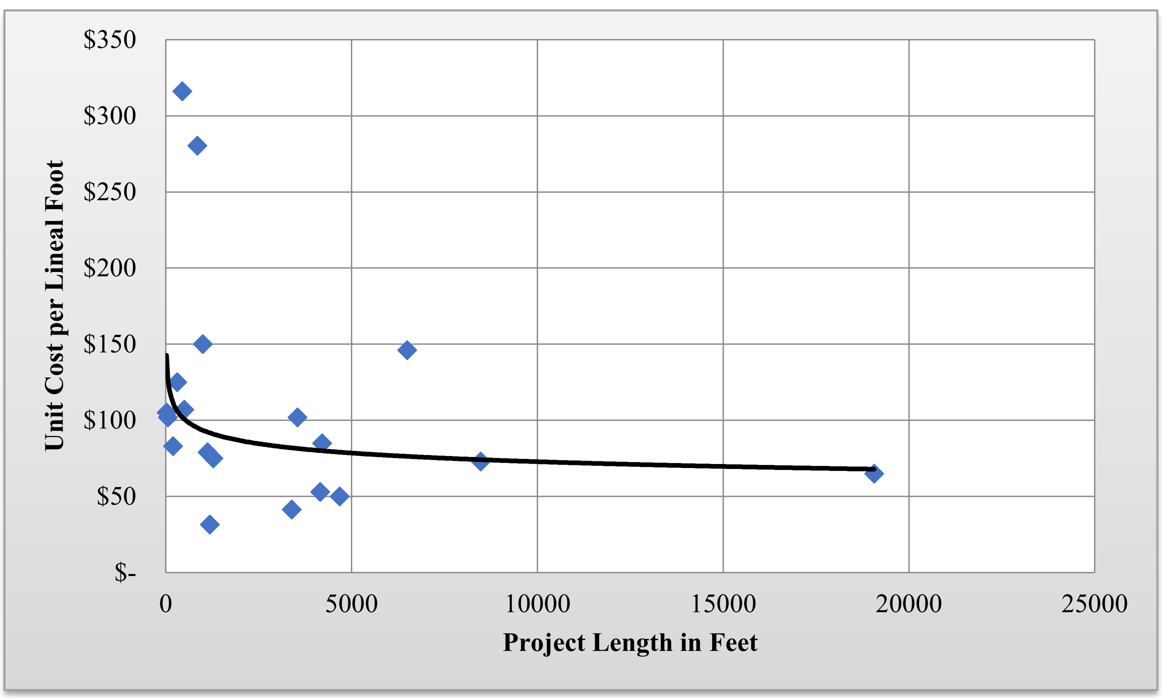

Figure A10. Pipe Bursting Work Unit Cost by Pipeline Diameter

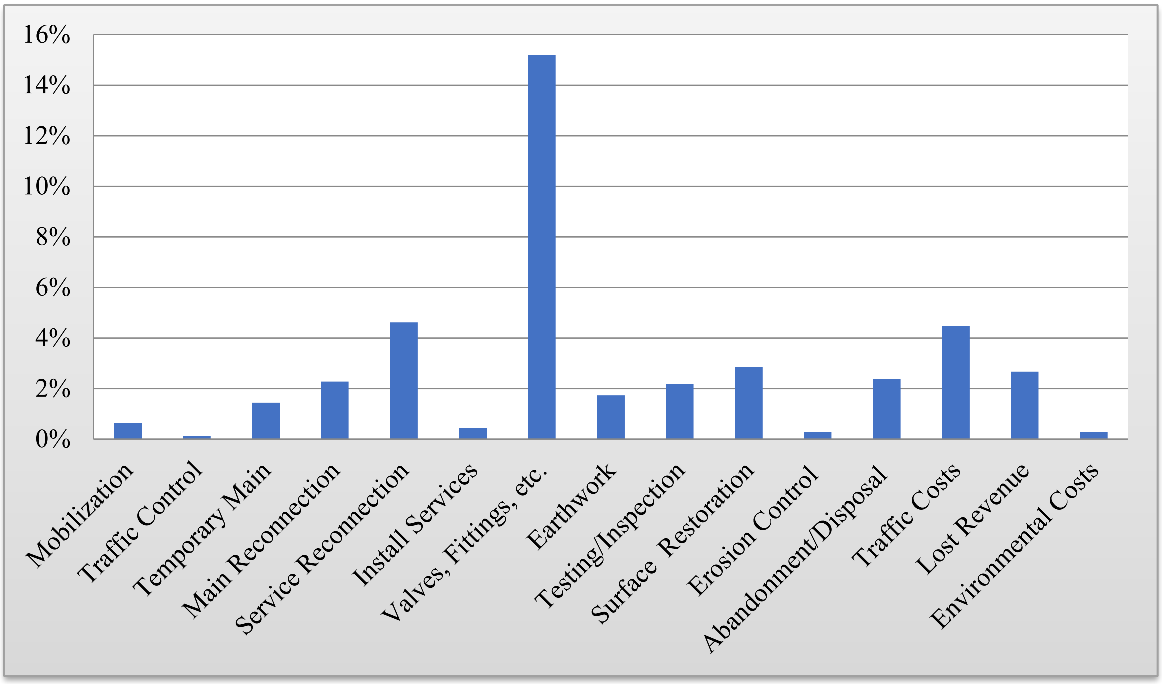

Figure A11. Supplemental Costs of Pipe Bursting Work by Percentage of Cost Burden

B. APPENDIX B DATA SOURCES

The research presented was built on one of the most comprehensive datasets in the United States, that of WATERiD and PIPEiD, projects completed by the SWIM Lab at Virginia Tech. The dataset laid the foundation for verifiable, calibrated, and finally validated modeling efforts across the uncertain conditions seen in the water utility space.

1. B.1 WATERiD Data Summary

- Source:
  - The Water Infrastructure Database (WATERiD, http:// waterid.org) was developed as a central, Web-based interactive database for water infrastructure systems in order to provide a standard platform through which institutional knowledge on several fronts could be shared; it was funded by National Science Foundation (NSF), the United States Environmental Protection Agency (U.S. EPA), and the Water Environment Research Foundation (WERF).

- Scope:
  - 190 case studies from over 30 U.S. drinking water utilities.
- Content:
  - Records include direct and indirect costs (e.g., labor, restoration, mobilization), pipeline attributes (material, diameter, depth), and technology used (e.g., CIPP, HDD, Open Cut).
- Limitations:
  - Sampling bias by using typically larger or more progressive utilities more apt to collaborate
  - Variations in unit costs across regions and in description.
  - Focus on established technologies vs. emerging ones

2. B.2 PIPEiD Data Summary

- Origin:
  - PIPEiD was developed by Virginia Tech and affiliated researchers to develop and test models and tools meant to improve water utility asset management.
- Coverage:
  - ~985,000 individual pipe segment records
  - ~37,000 documented failure events (leaks, bursts, corrosion)
  - Contributed by over 500 U.S. utilities
- Data Quality:
  - ~80% of records include break history or advanced condition assessment data.
  - Nearly 23,000 remaining wall thickness records.
- Geographic Scope: Urban utilities in the U.S. and Bureau of Reclamation data
- Handling of Missing Data:
  - Minor gaps (e.g., RWT or depth) addressed via mean substitution or engineering-informed imputation.

- Missing data flagged for sensitivity testing in Type 2 fuzzy logic model validation Quality:

3. B.3 Data Use and Ethics

- All data was anonymized in accordance with MOUs with utilities.
- Data was used solely for research purposes and utility input do not imply recommendations of endorsement of any tool

C. APPENDIX C USER GUIDE FOR MODEL IMPLEMENTATION

This appendix provides instructions to use the MATLAB-based Type 2 fuzzy logic model developed in this research for prioritizing drinking water main renewal strategies under uncertainty.

1. Step 1: Input Required Data

The model requires the following key inputs per pipe segment (from available GIS and maintenance data):

a) Physical Parameters

(1) Pipe Age (years)

(2) Material Type (classified 1–5, where 1 = best vintage, 5 = worst)

(3) Break History (# of failures)

(4) Remaining Wall Thickness (RWT, if available)

(5) C-Factor or Tuberculation

(6) Aggressive Index (AI) or similar water quality indicator

(7) Pressure, Fire Flow Adequacy

b) Economic Parameters

(1) Estimated cost of intervention (e.g., renewal, repair, replacement)

(2) Consequence factors (e.g., traffic disruption, customer impact, legal exposure)

(3) Spatial factors (e.g. depth of burial, flooding frequency, redundancy level)

2. Step 2: Fuzzy Priority Score and Interpretation

The model then assigns a priority score (ranging from 0.00 to 1.00) to each intervention that's repeated each year until one of the active methods' priority exceeds that of Do Nothing. Once the activity takes place the priority scores reset accordingly and the modeling process begins again.

- Do Nothing
- Inspect & Maintain
- Rehabilitation
- Replacement

3. Step 3: Dictate Renewal Plan

Categorize results by fuzzy priority category to create a Capital Improvement Plan (CIP):

- Rank segments by fuzzy score (low to high)
- Overlay with GIS to identify clusters, interdependencies, or red flags in critical areas such as hospitals or larger mains in highly urbanized areas
- Develop management strategies and budgets based on results

Example Case:

Input	Value
Pipe Age	65 years

Input	Value
Material	1 (early cast iron)
Breaks	3
RWT	50%
Aggressive Index	9.8 (aggressive)
Estimated Replacement Cost	$550/LF

Model Output:

Top Fuzzy Score = Inspect & Maintain

Estimated Timing: Immediately

MATLAB Fuzzy Model Code:

```
% METALLIC WATER MAINS using FUZZY ANALYSIS
% Input Variables
clear all;
   % Read all rows at once
   [pmtl, pbrk, regn, trfc] = readvars(fname, 'Range', 'CT:CW');
   [pdep, pobs, wthr] = readvars(fname, 'Range', 'CX:CZ');
   [pdia, plen, rddc, lstint] = readvars(fname, 'Range', 'DA:DD');

   % Ensure data is numeric
   pmtl = cell2mat(pmtl);
   pbrk = cell2mat(pbrk);
   regn = cell2mat(regn);
   trfc = cell2mat(trfc);
   pdep = cell2mat(pdep);
   pobs = cell2mat(pobs);
   wthr = cell2mat(wthr);
   pdia = cell2mat(pdia);
   plen = cell2mat(plen);
   rddc = cell2mat(rddc);
   lstint = cell2mat(lstint);
end

% find total number of rows
Nrows = length(pmtl);

% initialize outplot.xlsx
writetable(table(), 'outplot.xlsx', 'Sheet', 1)

% loop to read rows from excel file
```

```
for k = 1:Nrows
    % prepare variables for fuzzy inference system
    trfc(k) = trfc(k) / 10000;
    plen(k) = plen(k) / 100;
    rddc(k) = 4 - rddc(k); % invert the redundancy

    % aggregate the variables into the respective modules
    dg_in = [pmtl(k) pbrk(k) regn(k) trfc(k)];
    df_in = [pdep(k) pobs(k) trfc(k) wthr(k)];

    % Load fuzzy inference system from files
    dg_fis = readfis('Degradation');
    df_fis = readfis('Obstruction');
    ri_fis = readfis('risk');

    % Load management strategy modules from files
    dn_fis = readfis('DN');
    im_fis = readfis('I&M');
    tr_fis = readfis('Trenchless');
    oc_fis = readfis('Replace');

    % Evaluate the Degradation and Difficulty modules
    dg_idx = evalfis(dg_fis, dg_in);
    df_idx = evalfis(df_fis, df_in);

    % Initialize variables before loop
    trsk = 0; % counter for risk time
    n = 1; % counter for physical time
    m = 1; % counter for resets
    xtb = table;
        dnpr = [];
    impr = [];
    trpr = [];
    ocpr = [];
    time = [];
    xmd = strings(1, 200); % preallocate for up to 200 iterations

    while true
        % risk module from the last intervention time
        risk_in = [pdia(k) plen(k) rddc(k) lstint(k) + trsk];
        risk_idx = evalfis(ri_fis, risk_in);

        % Do Nothing
        dn_in = 5 - [dg_idx df_idx risk_idx]; % invert all scores
        dnpr(n) = evalfis(dn_fis, dn_in);

        % Inspect and Maintain
        im_in = [5 - dg_idx df_idx risk_idx]; % invert degradation
        impr(n) = evalfis(im_fis, im_in);

        % Trenchless Refurbishment
```

```
tr_in = [dg_idx df_idx risk_idx];
trpr(n) = evalfis(tr_fis, tr_in);

% Open Cut Replacement
oc_in = [dg_idx 5 - df_idx risk_idx]; % invert difficulty
ocpr(n) = evalfis(oc_fis, oc_in);

% Record time in years starting with 0 years
time(n) = n - 1;
trsk = trsk + 1;

% record crossing of management strategies
xmd(n) = "";

% Check do nothing against others
imck = dnpr(n) - impr(n);
trck = dnpr(n) - trpr(n);
occk = dnpr(n) - ocpr(n);

% If do nothing crosses other conditions
if n >= 200
   xtime(m) = time(n);
   xstrgy(m) = "No Cross";
   xmd(n) = "No Cross";
   xtb = addvars(xtb, time(n), "No Cross");
   break
elseif (imck < 1e-3) || (trck < 1e-3) || (occk < 1e-3)
   % Record time that it crosses the do nothing strategy
   xtime(m) = time(n);

   if (imck < 1e-3)
      xstrgy(m) = "IM";
      xtb = addvars(xtb, time(n), "IM");
      xmd(n) = "IM";
   elseif (trck < 1e-3)
      xstrgy(m) = "TR";
      xtb = addvars(xtb, time(n), "TR");
      xmd(n) = "TR";
      % Set pipe material to 2
      pmtl(k) = 2;
   elseif (occk < 1e-3)
      xstrgy(m) = "OC";
      xtb = addvars(xtb, time(n), "OC");
      xmd(n) = "OC";
      % Set pipe material to 2
      pmtl(k) = 2;
   end

   % reset degradation module
   dg_in = [pmtl(k) pbrk(k) regn(k) trfc(k)];
   dg_idx = evalfis(dg_fis, dg_in);
```

```
            % time for risk reset
            trsk = 0;
            m = m + 1;
        end

        % increment time counter
        n = n + 1;
    end

    if choosein == 1
        % plot management strategies vs time for one row
        plot(time, dnpr, 'b', time, impr, 'r', time, trpr, 'k', time, ocpr, 'y')
        legend('DN', 'I&M', 'TR', 'OC')
        xlabel('time')
    else
        % workaround for writing strategies
        xtb

        % write plot variables for each row on separate sheet
        plttb = table(time', dnpr', impr', trpr', ocpr', xmd');
        writetable(plttb, 'outplot.xlsx', 'Sheet', num2str(k), 'WriteMode', 'overwritesheet');

        % write strategies on excel sheet when resets
        wr_rg = append('DE', num2str(k + 1));
        writetable(xtb, fname, 'WriteVariableNames', false, 'Range', wr_rg);
    end
end
```

Sample MATLAB membership function code (all code available upon request):

```
[System]

Name='Replace24'

Type='mamdani'

Version=2.0

NumInputs=3

NumOutputs=1

NumRules=15

AndMethod='min'

OrMethod='max'

ImpMethod='min'
```

```
AggMethod='max'
DefuzzMethod='centroid'

[Input1]
Name='LoF_Index'
Range=[1 5]
NumMFs=5
MF1='Excellent':'trapmf',[0.4 0.8 2.3 2.9]
MF2='Fair':'trimf',[3.0 3.5 4.0]
MF3='Poor':'trimf',[3.5 4.0 4.3 4.5]  % Lower threshold for earlier trigger
MF4='Good':'trimf',[2.5 3.0 3.5]
MF5='Very_Poor':'trapmf',[4.0 4.5 5.0 5.5]  % Increased sensitivity to severe LoF

[Input2]
Name='CoF_Index'
Range=[0 5]
NumMFs=5
MF1='Excellent':'trapmf',[-0.7 -0.4 1.0 2.0]
MF2='Good':'trapmf',[0.9 1.5 2.0 2.5]
MF3='Fair':'trapmf',[2.3 2.8 3.3 3.8]
MF4='Poor':'trapmf',[3.2 3.7 4.2 4.7]  % More responsive to high CoF
MF5='Very_Poor':'trapmf',[4.0 4.5 5.0 5.5]

[Input3]
Name='Time_Step'
Range=[0 5]
NumMFs=5
MF1='Very_Low':'trapmf',[-1.5 -1 1.5 2.2]   % More responsive to early replacement
MF2='Low':'trimf',[1.1 2.0 2.9]
MF3='Fair':'trimf',[2.8 3.5 4.0]
```

MF4='High':'trimf',[3.5 4.2 4.8]

MF5='Very_High':'trapmf',[4.0 4.5 7.0 7.5]

[Output1]

Name='OC'

Range=[0 1]

NumMFs=5

MF1='Very_Low':'trapmf',[0.15 0.2 0.25 0.3]

MF2='Low':'trimf',[0.3 0.4 0.5]

MF3='Fair':'trimf',[0.45 0.55 0.65]

MF4='High':'trimf',[0.6 0.7 0.8]

MF5='Very_High':'trapmf',[0.75 0.85 1.05 1.15]

[Rules]

0 0 1, 1 (1) : 1

0 0 2, 2 (1) : 1

0 0 3, 3 (1) : 1

0 0 4, 4 (1) : 1

0 0 5, 5 (1) : 1

0 1 0, 5 (0.2) : 1

0 5 0, 2 (0.2) : 1

0 4 0, 3 (0.4) : 1

0 3 0, 4 (0.6) : 1

0 2 0, 5 (1) : 1

1 0 0, 1 (0.2) : 1

4 0 0, 2 (0.2) : 1

2 0 0, 3 (0.2) : 1

3 0 0, 4 (0.2) : 1

5 0 0, 5 (0.2) : 1