Automating Water Capital Activities Using Naïve Bayes Classifier with Supervised Learning Algorithm

by

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Author's Declaration

This thesis consists of material, all of which I authored: see Statement of Contributions included in the thesis.

This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

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Statement of Contribution

Chapters 2, 3, 4 and 5 of this thesis have been incorporated into to publish papers co-authored by myself and my supervisors, Dr. Mark Knight and Dr. Andre Unger. The survey questioner presented in Appendix A1is prepared by myself with the help of my supervisors Dr. Mark Knight and Dr. Andre Unger. This survey is organized in The Survey Monkey site belongs to the Canadian Association of Trenchless Technology (CATT). This survey is advertised in the water industry with the help of Dr. Rizwan Younis, technical director of CATT.

Abstract

Municipal governments have the responsibility to provide safe drinking water to residents. Maintaining water infrastructure systems to keep a certain level of service is a vital service. It is possible by assessing all assets and planning capital work activities to renew and renovate the existing assets. The municipalities prioritize the capital activities of their infrastructure and are required to optimize their available resources.

Past studies confirmed due to several complexities and imperfections of the available water network data, there is a need for a comprehensive multicriteria database to prioritize pipe capital plan decisions based on engineering expert judgment. This database must include information about water pipe physical condition and performance up to an acceptable level of service and criticality based on the water pipe location. In addition, the lack of standard regulatory requirements due to incomplete condition, criticality and performance assessment of the entire Municipal Water Network (MWN) leads to bias and undefendable engineering judgment. Although several pipe prioritization models have been developed and published in the literature, no comprehensive multi-decision criterion model is available to date, including the pipe segment condition, performance, and criticality.

In this research, a novel Priority Action Number (PAN) is developed and parameterized based on pipe segment condition, performance and criticality. An automated Naïve Bayes Classifier (NBC) with a supervised machine learning model is proposed for consistent, defensible and personnel independence ranking of existing water pipe condition, performance, and criticality of all water pipes through MWN. This methodology automates the capital activities decision-making process. The research presents and develops a prioritizing approach for the MWN capital activities and aids in selecting assistive technology for rehabilitation and renewal capital activities.

The developed model is applied to the City of London MWN database in a Geographical Information System (ArcGIS) database to validate and verify the model. The multi-level classifier model classified and assigned a capital work activity to all pipes in the City of London MWN.

The presented multi-level NBC with a supervised learning algorithm replicates the expert's opinion and engineering judgement. Through NBC supervised machine learning algorithm, the capital project decision-making process is automated. This methodology will add consistency and defensibility to capital programs. Using this algorithm can help utility save money by automating industry best practices and optimizing long-term decisions about the order in which pipes need to be staged into capital works programs.

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I would like to express my sincere gratitude and deepest appreciation to my supervisors Dr. Andre Unger and Dr. Mark Knight, for their kind advice and exceptional mentorship throughout my PhD program. This research truly benefited from their constant encouragement and support of my ideas. I am also thankful to Dr. Mahesh Pandey, Dr. Chris Bachmann, and Dr. Mohammad Kohandel as my committee members to review my research proposal and thesis and offer insightful comments. It is a privilege to have Dr. Jayantha Kumarasiri Kodikara as my External Examiner and reviewer of my thesis, and I am very grateful.

I would also like to acknowledge the City of London for making available their data for this research. Many staff members in these cities, especially Mr. Kevin Graham, found time to meet and discuss my research and offer useful insights despite their hectic schedules.

I would like to express my special gratitude to my dear family for their encouragement and for all of their warmth and care. My heartfelt gratitude goes to my husband for her love, companionship and patience throughout our amazing journey.

Dedication

To my beloved husband, son and daughter

Soheil, Rodman and Kiana

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Chapter 1

1.1 Background

The Canadian Infrastructure Report Card (2012) estimates the replacement value of water assets to be $362 billion. Lack of effective and proactive capital work activities has resulted in this huge infrastructure backlog over the past decade. To reduce this backlog and to stop its growth, massive infrastructure investments are required. To generate revenue for these investments, utilities are required to rapidly increase the cost of water to their customers (residents and businesses). This rapid cost increase often results in affordability issues, especially for low-income families and businesses. Ontario Regulation 453/07 (MEO, 2007) and Public Sector Accounting Board (PSAB) Statement 3150 (CICA, 2007) require all public water utilities to prepare annual reports on the current and the future condition of their in-service assets. Managing ageing water infrastructure systems with limited financial resources requires comprehensive multicriteria decision support methodology to make defensible capital activity decisions for all Municipal Water Network (MWN) assets to maintain and/or enhance service levels.

This research uses Artificial Intelligence (AI) to automate the classification activity for all pipes within MWN for condition, performance, criticality and assign a capital work activity. A Naïve Bayes Classifier (NBC) with a supervised learning algorithm is employed to automate the capital planning activities for MWN. The supervised learning algorithm uses the responses obtained from an expert survey developed and analyzed as part of this research project; these expert's opinions are used as target values to parameterize the NBC model.

A novel Priority Action Number (PAN) is developed and parameterized based on pipe segment Condition, Performance and Criticality Score. Models are applied in a Geographic Information System (ArcGIS) with the geospatial capability to identify each pipe within MWN for all criteria. The model is developed to run on very large MWN in southern Ontario municipality and tested on the City of London MWN. The results are validated with the City of London water replacement program for 2016 and 2017.

The proposed methodology develops a standardized decision-making framework that allows for defensible, repeatable and auditable prioritization decisions that are automated and implemented into an ArcGIS system. The prioritization model is based on expert opinion using a machine learning algorithm.

Prioritizing capital activities requires considerations of several variables and attributes. The common strategy prioritizing capital work decisions involved linear asset physical condition attributes, and other attributes such as pipe performance and criticality are neglected (OSWCA, 2018). The common theme of the current methodology is focused on one type of mitigation decision, such as rehabilitation and replacement of water infrastructure (Halfawy & Hengmeechai, 2014). North American municipalities are struggling to develop tools and processes that respond to the problem proactively instead of reactively (Kumar, et al., 2018). An important barrier to a proactive capital program is the lack of standard regulatory requirements due to complete condition, criticality and performance assessment of the entire system. Municipalities are following a different decision-making technique developed by their internal municipal engineer. While engineering judgements are subjective, it's required to be supported by consistent decision-making methodology (Aven, 2016). Often the engineer judgements are questioned by elected officials in each City due to capital activity price tag and dollar values.

Municipalities spend billions of dollars assessing linear infrastructure and planning capital works activities to provide sufficient support for capital activities decisions. By automating capital activity decision-making processes, not only consistency repeatability and defence-ability would be added to capital activities decisions, but also the resources can be spending on much-needed water asset maintenance activities. This study proposes a decision support tool that would add consistency and defence-ability to capital activity decisions.

1.2 Research Goal and Objectives

The overall goal of this research is to propose a novel framework for a comprehensive multicriteria methodology to automate planning of the water capital activities, prioritize them with a scientific methodology and demonstrate its application merits on the City of London.

This goal is achieved by pursuing eight specific research objectives as follows:

1. Review the available frameworks assessing water pipes for capital activities to identify attributes affecting condition, performance and criticality.
2. Define a multicriteria framework assessing all pipes in the MWN for their condition, performance, criticality and suggesting a capital work mitigation methodology to all pipes in the MWN.
3. Propose a novel Priority Action Number (PAN) to prioritize the proposed capital activity to all pipes within the MWN.
4. Prepare a survey gathering expert's opinion on the water pipe's condition, performance, criticality, and assigning a water capital activity in a systematic approach to the supervised machine learning algorithm.
5. Define a Naïve Bayes Classifier with a supervised machine learning algorithm to automate the water pipe assessment for condition, performance and criticality (level 1 - Prioritization Model).
6. Define a Naïve Bayes Classifier with a supervised machine learning algorithm to assign capital activities to all pipes in the MWN calibrated to the expert's opinion (level 2 - Mitigation Model).
7. Demonstrate the proposed framework's application and apply the developed NBC with a supervised machine learning model using a case study on an existing the MWN database.
8. Validating the NBC with a supervised machine learning model with the comparison with an actual municipal engineer prepared watermain replacement program.

1.3 Thesis Organization

This thesis is organized in an integrated-article format – that is, each of Chapters 2 to 5 addresses one or several of the above-listed research objectives. Figure 1-1 presents a graphical summary of the remainder of the thesis chapters and the main research tasks performed in each of them.

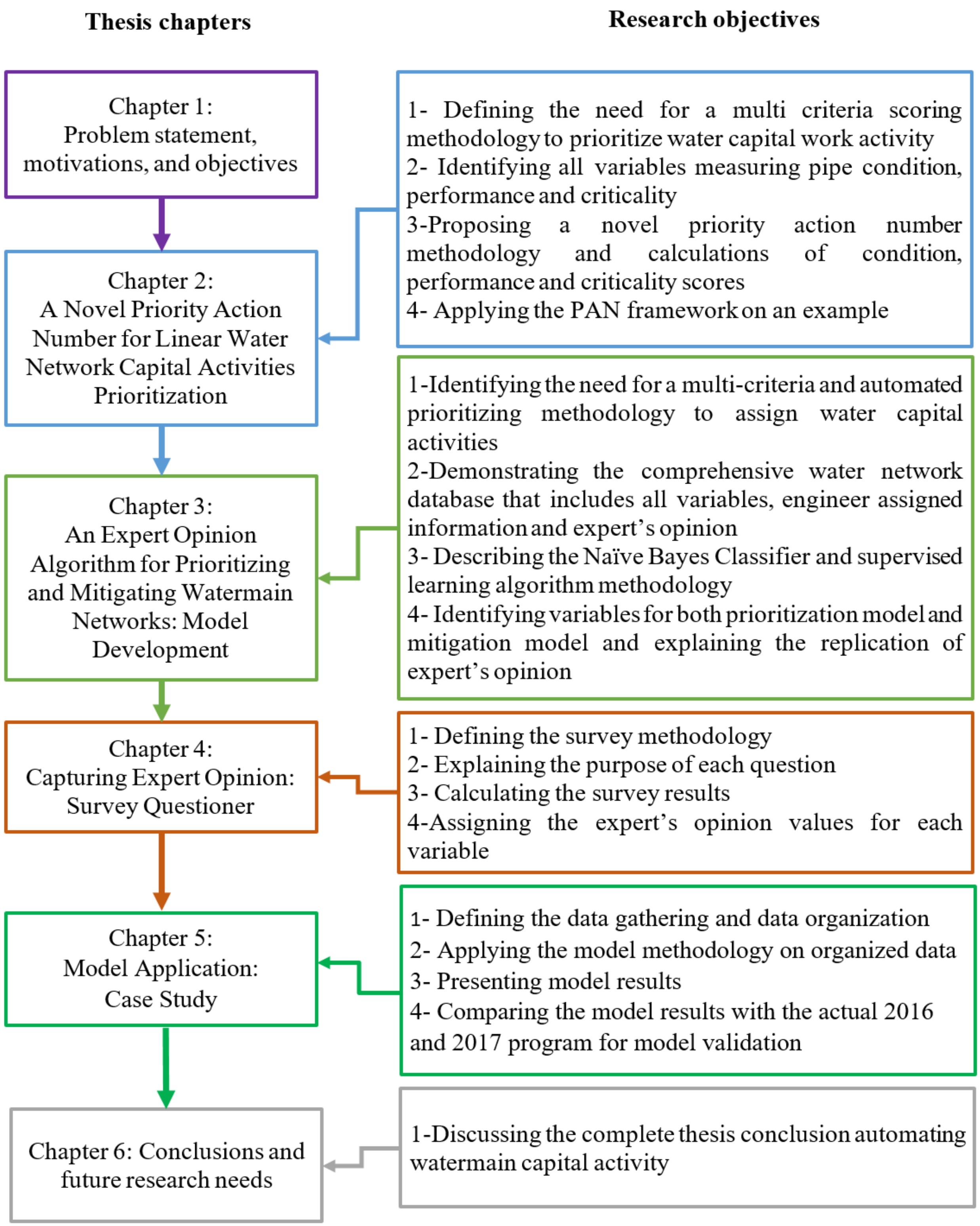

Figure 1-1 Thesis chapters organization and objectives.

Chapter 2 presents the Priority Action Number (PAN) that is developed and parameterized based on pipe segment Condition, Performance and Criticality Score. Scores are developed so that higher Scores and a higher PAN indicate higher priority for the pipe segment replacement or rehabilitation. Two scenarios are presented to demonstrate how the PAN is determined and how it can be used in an automated computer program and/or ArcGIS program to establish defensible and auditable pipe segment replacement decisions for a water network.

Chapter 3 presents a prioritizing approach for the watermain networks' capital activities and aids in selecting assistive technology for rehabilitation and renewal. Using a MWN comprehensive database that is mapped in an ArcGIS system, a machine learning classifier model is proposed to classify all pipes in the MWN and assign a capital work activity. The capital project decision-making process is automated through the NBC supervised learning algorithm.

In Chapter 4, a survey questioner is presented. The survey obtains expert opinion using a set of standardized questions framework on prioritizing municipal water network capital activities. This methodology will add consistency and defensibility to capital programs.

In Chapter 5, a descriptive analysis of the water network pipes is presented for their condition, performance and criticality, including capital planning decisions regarding all pipe within the London database. Different maintenance and capital work scenarios are presented and compared with the actual 2016 and 2017 replacement programs from the City of London to verify and validate the model.

Chapter 6 presents a general summary of conclusions, original contributions to the state of knowledge, and directions for future research.

Chapter 2

A Novel Priority Action Number for Linear Water Network Capital Activities Prioritization

Abstract

Most water utilities in North America have a massive backlog of deteriorated and aged watermains and are faced with the daunting task of determining which pipe segments need replacement and rehabilitation now. Although many pipe prioritization models have been developed and published in the literature, no capital activity prioritizing model is available to date that is based on a multi-decision criterion that includes the pipe segment condition, performance, and criticality. In this chapter, a Priority Action Number (PAN) is developed and parameterized based on pipe segment Condition, Performance and Criticality Score. The score is developed so that higher scores and a higher PAN indicate higher priority for the pipe segment replacement or rehabilitation. Two Scenarios are presented to demonstrate how the PAN is determined and how it can be used in an automated computer program and/or ArcGIS program to establish defensible and auditable pipe segment replacement decisions for a water network.

Keywords: watermain, capital works activities, asset management, municipal water network, prioritization, condition, water pipe performance, water pipe criticality, number of breaks, mitigation technology

2.1 Introduction

Watermain transmission and distribution pipes are the arteries and veins of a water utility system that supply potable water from treatment plants to businesses and homes and provide water for fire protection. The construction of these pressured water distribution networks started in the late 1800s mainly as a fire protection system. Once constructed, it did not take long for them to also be used to supply drinking water to homes and businesses. Today, most North American water systems are still designed for both purposes.

Over the past 150 plus years, city boundaries have expanded, and the length and size of these water distribution networks have expanded exponentially with little maintenance, replacement and/ or renovation. Thus, many cities have hundreds of kilometres of water pipes in service that have exceeded their design life of 50 to 100 years. This backlog of deteriorated infrastructure has resulted in a significant number of annual watermain breaks with ever-increasing operational and maintenance expenditures. For example, corrosion of end-of-life cast iron and ductile iron pipes in the City of Toronto has resulted in over 4000 watermain breaks in 2018 alone, with an annual repair cost of over $20 million. Because most cities in North America have set user fees to recover operational costs only, limited capital funds are available to replace ageing, deteriorating and failing watermain pipes. This lack of capital works continues the cycle of the growing infrastructure backlog. To resolve this issue, municipalities have started the process to prioritize which pipes in their network need to be replaced immediately relative to those targeted for replacement as part of later projects and allocating capital to fund these replacement programs.

Several methods have been proposed in the published literature to rank and prioritize pipes for replacement. Table 1-1 provides a review and analysis of the published research literature based on four pipe prioritization methods and three pipe ranking criteria. These prioritization methods are: (a) individual pipe segments using a cost-benefit analysis; (b) network-wide pipe segments using a cost-benefit analysis; (c) statistical analysis using pipe age, material type, and/or location; and (d) classify and score pipe attributes such as material, type, age or other pipe properties such as size, location, etc.. The three ranking criteria for individual pipe segments are: (1) condition, (2) performance, and (3) criticality. Condition is a measure of the physical properties of a watermain pipe, such as water pipe material and number of breaks. According to the Ontario best practice

OSWCA (2018), the condition is the degree of structural deterioration of the water pipe. The most common type of physical assessment is the age of the pipe segment. However, some municipalities are moving towards assessing alternative physical attributes instead of relying on age only (OSWCA, 2018). Pipe performance measures the ability of a watermain segment to comply with all regulatory guidelines for operating a water system while delivering acceptable Levels of Service (NRC•CNRC, 2007). Finally, pipe criticality measures the relative importance of a given water pipe to be able to provide acceptable Levels of Service to consumers (WRc, 2011). For example, a watermain pipe that provides service to a hospital is more critical than one that provides service to a few single-family dwellings along a residential road.

Shamir and Howard (1979) and Walski (1987) began the process of ranking and prioritizing maintenance activities of individual pipe segments. For example, they considered the cost-benefit of whether incurring the capital expense of replacing a pipe segment has greater beneficial value than maintaining its current service level, based on its annual operational and maintenance expenditures (NRC•CNRC, 2003). This type of planning is called "age-based" (OSWCA, 2018) because the cost-benefit calculation requires the water pipe segment's expected remaining life. Thereafter, Kleiner and Rajani (2008), Hong et al. (2006), Loganathan et al. (2002), Kleiner and Rajani (2001), Walski (1987) and Shamir and Howard (1979) used the cost-benefit analysis method based on pipe condition to determine the optimized ratio for individual pipe repair and replacement. A limitation of the individual cost-benefit analysis method is that it can only be used until the number of water pipes requiring capital activities does not exceed the municipality budget's capacity. For instance, if the number of watermain pipe replacement activities targeted for delivery in a certain year exceeds the utility resources to perform the activities, then further prioritization needs to be undertaken to limit capital expenditures. Therefore, there is a need to look at the water network as a whole rather than as a collection of individual pipe segments (AWWA, 2012).

Table 2-1 Water System Prioritization Methods with Pipe Ranking Criteria

Prioritization Method	***Ranking Criteria***		
	Condition	***Performance***	***Criticality***
1- Ranking Individual Pipe Segments using a Cost-Benefit Analysis			
Kleiner & Rajani, 2008	✓	×	×
Hong et al., 2006	✓	×	×
Loganathan et al., 2002	✓	×	×
Kleiner & Rajani, 2001	✓	×	×
2- Network Wide Pipe Ranking using a Cost-Benefit Analysis			
Moglia et al., 2006	✓	×	×
Sægrov et al., 2003	✓	×	×
Burn et al., 2003	✓	×	×
3- Statistical Analysis			
Xu et al., 2013	✓	×	×
Rogers, 2011	✓	×	×
Zayed & Fares, 2010	✓	×	×
Kleiner et al., 2010	✓	×	×
Saldarriaga et al., 2010	✓	×	×
Giustolisi et al., 2009	✓	×	×
Berardi et al., 2008	✓	×	×
Kleiner et al., 2006	✓	×	×
Dandy & Engelhardt, 2001	✓	×	×

Kleiner et al., 1998	✓	✓	×
4- Scoring Methods Based on a Pipe Segments Physical Properties			
Asnaashari et al., 2013	✓	×	×
Wang et al., 2009	✓	×	×
Boxall et al., 2007	✓	×	×
Al Barqawi & Zayed, 2006	✓	✓	✓
Ranjani et al., 2006	✓	×	×
Milhot et al., 2003	✓	×	×

Moglia et al. (2006), Sægrov et al. (2003), Burn et al. (2003) and Deb et al. (1998) developed a network-wide pipe ranking approach utilizing a cost-benefit ratio based on the condition of individual pipe segments. Their methodology follows an age-based analysis comparing the cost-benefit ratio for pipe replacement and/or rehabilitation relative to maintaining the pipe network in a minimum condition. While this approach does prioritize maintenance activities subject to financial constraints (OSWCA, 2018), the ranking of pipe segments is done without considering the criticality of a given pipe segment service within the network. Moreover, many other parameters are required for accurate prioritization of watermain segments within a network.

Statistical models attempt to prioritize maintenance activities for watermain pipe segments by using physical properties such as age, number of breaks, soil conditions, and pipe internal deterioration factors to predict their expected failure time. Berardi et al. (2008), Saldarriaga et al. (2010), Rogers (2011) and Xu et al. (2013) used the pipe break rate as a variable to prioritize replacement. Zayed and Fares (2010), Kleiner et al. (2010) and Kleiner et al. (2006) proposed correlations between soil conditions and pipe corrosion to prioritize replacement. Dandy and Engelhardt (2001) used optimization strategies utilizing statistical models of physical properties to minimize maintenance costs and to predict pipe replacement time. Therafter, Giustolisi et al. (2009) used economic models based on pipe age to prioritize watermain replacement. Kleiner et al. (1998) combined watermain pipe hydraulic and age-based physical properties and pipe performance parameters to develop a cost-benefit analysis for individual pipe segments in a network. Statistical models have not been used to prioritize watermain pipe segments for rehabilitation technologies rather than replacement. Additionally, statistical models have not considered the type and criticality of the account type that they service when prioritizing maintenance activities.

Another common strategy to prioritizing maintenance and capital work decisions involves scoring and ranking individual pipe segments based on attributes related to their physical condition, such as age, break rate, pipe material, pipe diameter and soil conditions (OSWCA, 2018). Asnaashari et al. (2013), Wang et al. (2009), and Kleiner et al. (2006) considered pipe diameter, pipe age, break rate and pipe material to classify and rank watermains when prioritizing pipe replacement. Boxall et al. (2007) and Mailhot et al. (2003) focused on ranking cast iron (CI) pipes for a replacement program. Al Barqawi and Zeyed (2006) considered condition, performance and criticality measurements to score and rank pipe segments. These measurements include condition factors such as: material, age, diameter, and past maintenance; criticality factors such as: soil type, pipe location, and disturbance (crossings); and performance factors such as: water pressure, water quality, and water flow. The objective of their work is to score and rank individual pipe segments to prioritize water capital activities. However, they did not consider capital works activities such as rehabilitation and/or replacement. The main objective for these models was the pipe deterioration rating for identifying which pipe would experience more breakage or which factor is more critical on water pipe deterioration.

This study aims to present a framework for the development of a novel Priority Action Number (PAN) that scores and ranks watermain pipe segments to prioritize them for mitigation activities such as rehabilitation and/or replacement. The PAN is comprised of independent attributes of a given pipe segment that contribute to the condition, performance, and criticality scores. The sum of these scores is the PAN. The outcome of the PAN is to be able to design a consistent, defensible, repeatable, and auditable set of rules that can be implemented and automated as an algorithm within computer programs with a framework such as ArcGIS. Thereafter, the PAN for all pipe segments in the network can be used to develop projects and programs to resolve the infrastructure backlog that utilities face regarding their inventory of watermain assets.

The following sections present the main components of the PAN and explain in detail: an itemized list of all variables contributing towards the condition, performance and criticality scores; how these variables are separated into bins intervals and enumerated; and the processes of weighting these scores to calculate the PAN for each pipe segment. Two scenarios involving pipe segments with a varying condition, performance and criticality properties and hence scores are presented. Thereafter, these same scores are weighted to enumerate a PAN. Finally, the combination of condition, performance and criticality scores and PAN are then used to propose a mitigation method.

2.2 Priority Action Number

The Priority Action Number (PAN) is developed by calculating a Condition, Performance and Criticality Score for each pipe segment within the network. Water pipe segments are considered from node to node. For this research, a node constitutes a pipe junction, where two or more water pipes are connected. Pipe segments are deemed to be a standard unit irrespective that they can have no standard length.

The Condition Score, S_C, represents the physical condition of the segment, while the Performance Score, S_P , represents the measure of a pipe's ability to operate at and otherwise meet established Levels of Service. The Criticality Score, S_{C_r}, represents the impact of a pipe if service is lost, the likelihood of failure, and the consequences of failure, also known as risk of service loss. All Scores are assumed to be independent of each other. Thus, a change in one Score will not impact another Score. Each Score is enumerated using several key variables that are also independent of one another. Figure 2-1 presents key variables used to develop the Condition, Performance and Critically Scores. These variables are established to measure, evaluate and prioritize attributes representing the operation and maintenance required by each watermain pipe segment according to available standards and best practices (NRC•CNRC, 2005).

The *PAN* is calculated for each pipe segment using Equation 2-1:

$$PAN = S_C\, W_C + S_P\, W_P + \; S_{C_r} W_{Cr} \qquad 2\text{-}1$$

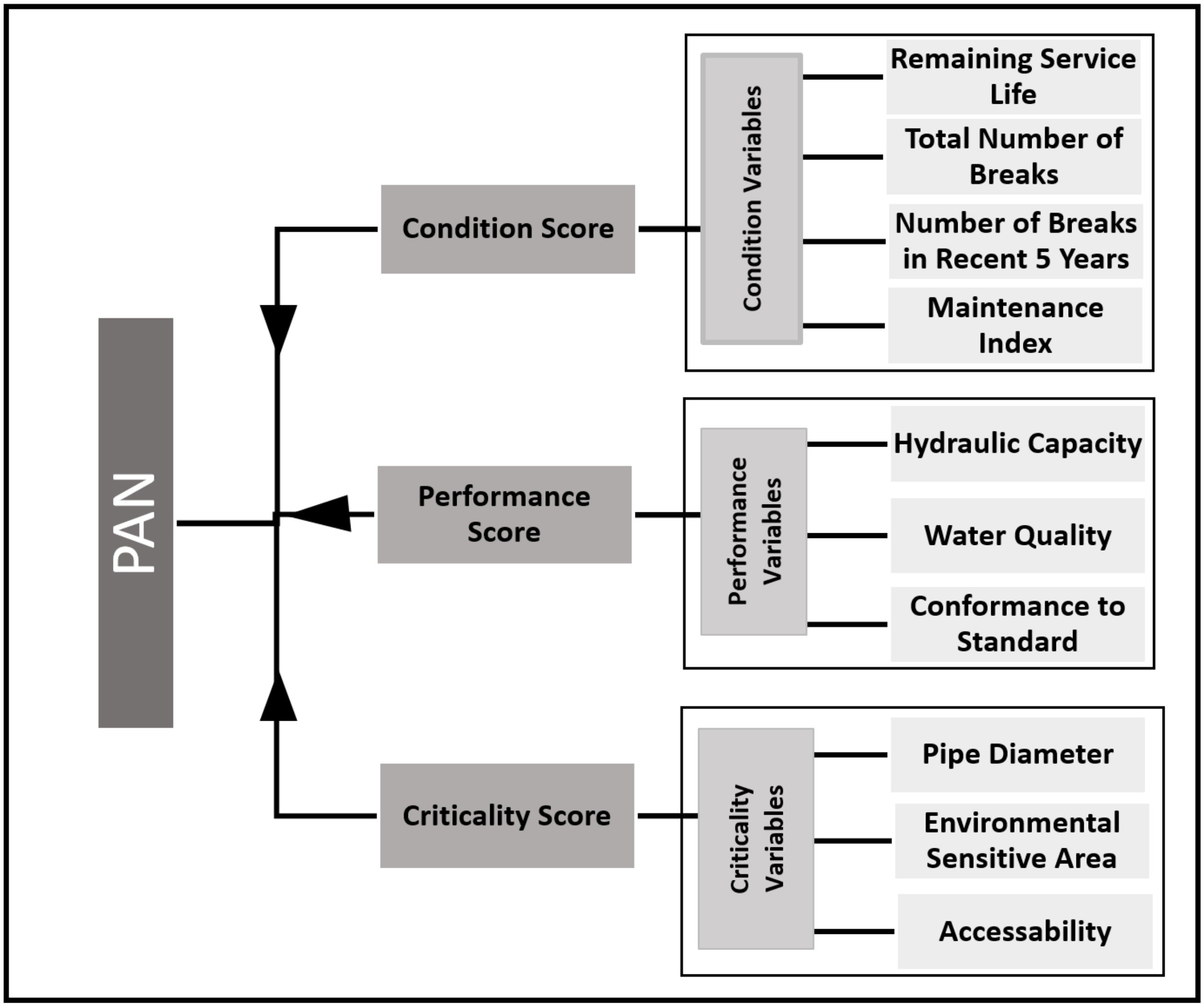

Figure 2-1 PAN Scores and variables

where W_C, W_P and W_{Cr} are the weighting factors for Condition, Performance and Criticality, respectively. Weighting factors are applied against each Score for two reasons. First, the relative importance of condition, performance and criticality may vary between water utility service providers as they attempt to prioritize each pipe segment for mitigation activity. Second, Figure 2-1 shows that each of the Condition, Performance and Criticality Scores is enumerated based on a different number of variables that contribute equally to a given score. Specifically, both Performance and Criticality Scores have three variables, while Condition Score has four. The weighing factor adjusts these disparities so that these variables contribute in relative proportion to the overall PAN. The outcome of the PAN Score for a given pipe segment is such that the higher its value is relative to other pipe segments in the prioritization list, the greater its need is for action in terms of rehabilitation or replacement.

The following sections describe the variables that contribute towards the Condition, Performance and Criticality Scores.

2.2.1 Condition Score (S_C)

Condition is a physical attribute of a pipe segment based on its structural and operational properties, such as water pressure, flow rate, external loads and water quality. Each property is assumed to be independent of the others. In the context of the Condition Score, the four properties, $\mathcal{P}$, are: (1) the Remaining Service Life, RSL; (2) the total number of breaks since installation, TB; (3) the total number of breaks in the last five years, TB_{5yrs}; and, (4) the maintenance index, MI. The contribution of each measured property to the Condition Score is quantified by $\mathcal{P}_{bin}$ into intervals, where the thresholds that bound these intervals have engineering significance based on standards or criteria relevant to each variable. The Condition Score variable, $V_{\mathcal{P}}$, is derived by applying a dimensionless weight to each bin, such that $V_{\mathcal{P}_{bin}} = f(\mathcal{P}_{bin})$. The Condition Score, $S_C = f\left(V_{\mathcal{P}_{bin}}\right)$, for each pipe segment, is a dependent variable on $V_{\mathcal{P}_{bin}}$ and is evaluated in Equation 2-2 as:

$$S_C = V_{RSL} + V_{TB} + V_{TB_{5yrs}} + V_{MI} \qquad \text{2-2}$$

Note that bin weightings for each of $V_{RSL}, V_{TB}, V_{TB_{5yrs}}$ and V_{MI} must be estimated subject to the constraint that the outcome of constructing the Condition Score is that an increase in S_C denotes the pipe segment should receive greater priority for replacement or rehabilitation.

2.2.1.1 Remaining Service Life (RSL)

Every watermain pipe segment is designed for an expected service life ($Expected\ Life$), which denotes the time, in years, from the installation of the pipe segment that will provide acceptable Levels of Service. For most pipes, this is 50 to 100 years.

The $Expected$d $Life$ of a water pipe will be reduced by corrosion. The corrosion rate depends on the type of pipe material and soil conditions around the pipe. Clay-type soils are known to be corrosive soil conditions (Kleiner et al., 2010). A dimensionless corrosive soil Reduction Factors ($\mathcal{R}_{\mathcal{M}}$), developed by Stradiotto (2016), are provided in Table 2-2. This reduction factor is used to reduce the pipe segment's expected life.

Table 2-2 Pipe Materials in Corrosive Soil Expected Life Reduction Factors.

Material Type $\mathcal{M}$	Reduction Factors $\mathcal{R}_{\mathcal{M}}$
Asbestos Cement (AC)	0.1
Cast Iron (CI)	0.3
Ductile Iron (DI)	0.5
PVC	0.1
Steel (ST)	0.3
CPP/CONC	1.0
HDPE	0.1

A watermain pipe segment Remaining Service Life (RSL) is the difference between the $Expected\ Life$ and the time, in years, the pipe has been in service ($Age\ in\ Service$). The RSL can be calculated using Equation 3 with $\mathcal{R}_{\mathcal{M}}$ obtained from Table 2-3 when the pipe is placed in corrosive soils and $\mathcal{R}_{\mathcal{M}}$ = 0 when the soils are not corrosive.

$$RSL = [Expected\ Life - (\mathcal{R}_M * Expected\ Life)] - Age\ in\ Service] \qquad 2\text{-}3$$

The Remaining Service Life variable V_{RSL} can be computed by binning the calculated RSL into four separate intervals, $V_{RSL,i}$, provided in Table 2-3.

Table 2-3 Remaining Service Life Bins

$RSL\ [years]$	$V_{RSL}\ [-]$
$RSL \leq 15\ years$	$V_{RSL,1}$

$15 < RSL \leq 30\ years$	$V_{RSL,2}$
$30 < RSL \leq 50\ years$	$V_{RSL,3}$
$RSL > 50\ years$	$V_{RSL,4} = 0$

The rationale for bounding the range of the four bin intervals is described as follows. The first bin occurs on the interval of $RSL \leq 15\ years$ to coincide with the typical maximum lifespan of a road surface. In this bin, planners would weigh the need to renovate or replace watermain pipe segments based on their condition during capital expenditure activities associated with the current road infrastructure. This bin would result in most weight placed on V_{RSL}. The second and third bin follows the same premise but under the second and third lifecycle of the road. Therefore, $V_{RSL,3} < V_{RSL,2} < V_{RSL,1}$, with all values dimensionless. If the design service life for watermain pipes is 70 years, a $RSL\ >\ 50\ years$ is effectively new and a $V_{RSL,4} = 0$ is assigned as shown in Table 2-3. V_{RSL} is a decreasing function as RSL increases.

2.2.1.2 Total Number of Breaks (TB)

Total breaks are a leading indicator of a given watermain pipe segment's condition (Al Barqawi & Zayed, 2006). It is also an important indicator for water utilities since it indicates a significant increase in Operational Expenses (OpEx) and service disruptions. The Total Number of Breaks (TB) is the total number of breaks since the pipe segment installation.

Once a pipe break occurs, normal operation and maintenance practice involve replacing or rehabilitating the standard pipe section in which the break has occurred. A standard pipe section that is constructed from PVC or HDPE is normally 8m long and is bounded by nodes/pipe junctions, where two water pipes are connected. Some municipalities normalize the total number of breaks by pipe section length or by either the age in service or expected service life of the pipe segment (Harvey, 2015). In the context of this study, TB is an integer number and not normalized by the pipe segment length. The rationale for not normalizing is that the entire pipe segment length serves a single functional purpose, and the objective is to place the entire pipe segment into a project for either replacement or rehabilitation.

The TB variable, V_{TB}, is computed by binning the calculated TB into four intervals, $V_{TB\ i}$, as shown in Table 2-4.

The rationale for bounding the range of the four bin intervals is described as follows. The TB before renovation or replacement varies between municipalities based on location and Levels of Service. Generally, due to costs associated with loss of service, municipalities target the replacement of a pipe segment between nine to eleven breaks since installation (Folkman, 2018). Here, the first bin denotes more than nine breaks since installation. This bin would result in the most weight placed on V_{TB}. The second and third bin motivate the utility provider to investigate the cause of the observed break events, although they do not necessitate the renovation or replacement of the pipe segment. Therefore, $V_{TB,1} > V_{TB,2} > V_{TB,3}$, with all values being dimensionless. Finally, when $TB = 0$, then $V_{TB,4} = 0$ and hence V_{TB} is a monotonically decreasing function as TB decreases.

Table 2-4 Bins for Total Number of Breaks

TB [$-$]	V_{TB} [$-$]
$TB \geq 9$	$V_{TB,1}$
$8 \geq TB \geq 5$	$V_{TB,2}$
$4 \geq TB \geq 1$	$V_{TB,3}$
$TB = 0$	$V_{TB,4} = 0$

2.2.1.3 Total Number of Breaks within the Last Five Years ($\boldsymbol{TB_{5yrs}}$)

The North American watermain break rates have increased by 27% per annum in recent years (Folkman, 2018). Number of breaks for a given pipe segment that have occurred within the last five years, TB_{5yrs}, identifies pipes with high Operational Expense (OpEx). TB_{5yrs} and its dependant variable, $V_{TB_{5yrs}}$, act as an indicator that the pipe is reaching the end of its lifespan. An increase in the break frequency suggests pipe segment failure in the future and a progressive increase in the OpEx (NRC•CNRC, 2007).

The total number of breaks within the last five years variable, $V_{TB_{5yrs}}$, is computed by binning the measured TB_{5yrs} into four separate intervals, $V_{TB_{5yrs},i}$, as itemized in Table 2-5.

A common practice is that more than one break per year in a pipe segment over the last five years is denoted as the worst acceptable condition by the utility provider NRC•CNRC (2007), and that pipe should be prioritized for immediate repair. Therefore, it is assigned the highest value, $V_{TB_{5yrs},1}$. Then, progressively smaller values are assigned to pipes that experience fewer breaks per year with $V_{TB_{5yrs},1} > V_{TB_{5yrs},2} > V_{TB_{5yrs},1}$. Finally, when $TB_{5yrs} = 0$, then $V_{TB_{5yrs},4} = 0$, and hence $V_{TB_{5yrs}}$ is a monotonically decreasing function as TB_{5yrs} decreases.

Table 2-5 summarizes the assigned bins and values for the number of breaks in the last five years.

Table 2-5 Bins for Number of Breaks within the Last Five Years

TB_{5yrs} $[per\ year]$	$V_{TB_{5yrs}}$ $[-]$
$TB_{5yrs} \geq 5$	$V_{TB_{5yrs},1}$
$4 \geq TB_{5yrs} \geq 3$	$V_{TB_{5yrs},2}$
$2 \geq TB_{5yrs} \geq 1$	$V_{TB_{5yrs},3}$
$TB_{5yrs} = 0$	$V_{TB_{5yrs},4} = 0$

2.2.1.4 Maintenance Index ($\boldsymbol{MI}$)

Maintenance activities are itemized as Operational Expenses ($OpEx$ [\$ $per\ annum$]) and include maintenance activities (flushing, regular inspection) and repair and rehabilitation (break/leakage repair) work conducted over the life cycle of the watermain asset. The Maintenance Index (MI) is defined in Equation 2-4 as the ratio of the net present value of $OpEx$ multiplied by the Remaining Service Life, RSL [$years$], and then divided by the pipe replacement capital expense, $CapEx$ [\$].

$$MI = (OpEx \times RSL)/CapEx \quad \text{2-4}$$

Each municipality has knowledge of its annual operation and maintenance expenses to forecast its annual budget requirements. According to Ontario's Long-Term Infrastructure Plan, published in December 2016, all Ontario Municipalities are required to have a 10-year plan. Therefore, all municipalities are required to assess their assets, including watermain infrastructure, at least once every ten years (NRC•CNRC, 2007). OpEx plus CapEx depend on the pipe diameter, length, and depth of the watermain pipe (NRC.CNRC, 2003). The average overall operation, maintenance and replacement cost per meter for general watermain pipes can be used for this index. An increasing value of MI indicates that the annual operational and maintenance costs aggregated over the Remaining Service Life of the pipe are greater than the renewal cost. Hence, an increase in MI can be used to prioritize a pipe for replacement.

The Maintenance Index variable, V_{MI}, is computed by binning the calculated MI into three separate intervals, $V_{MI,i}$, as shown in Table 2-6. Common practice denotes that if the operating expenses of a pipe segment over its Remaining Service Life are more than five times greater than the capital expense of replacing the pipe segment, then the pipe should be replaced (NRC•CNRC, 2005). Therefore, the hierarchy of the assigned values are: $V_{MI,1} > V_{MI,2} > V_{MI,3}$, with all values being dimensionless. All MI assigned bins and values are provided in Table 2-6.

Table 2-6 Assigned Bins for Maintenance Index

MI [−]	V_{MI} [−]
$MI \leq 0.01$	$V_{MI,1}$
$0.01 < MI \leq 0.05$	$V_{MI,2}$
$MI > 0.05$	$V_{MI,3}$

2.2.2 Performance Score ($\boldsymbol{S_P}$)

Pipe performance measures the ability of a watermain segment to comply with all guidelines for operating a water system while delivering acceptable Levels of Service (NRC•CNRC, 2007). Relevant properties are associated with Performance such that $V_{\mathcal{P}_{bin}} = f(\mathcal{P}_{bin})$. The Performance Score, $S_P = f\left(V_{\mathcal{P}_{bin}}\right)$, for each pipe segment is a dependant variable on $V_{\mathcal{P}_{bin}}$ and is determined using Equation 2-5.

$$S_P = V_{PL} + V_{WQ} + V_{CLS} \qquad \text{2-5}$$

Bin weightings variables are constructed such that an increase in S_C denotes that the pipe segment should receive greater priority for replacement or rehabilitation.

2.2.2.1 Water Pressure Loss ($\boldsymbol{PL}$)

Hydraulic properties relevant to quantifying pipe performance include capacity, head loss, flow velocity, and pressure. Pipe performance is associated with its ability to provide a service, such as the need for water pressure to remain above 690 kPa at all locations within the network to comply with the Ontario Fire Marshal Guideline (OFM-TG-03, 1999). This study focuses on pressure loss as the performance criterion for transmission mains, distribution feeder-mains, and local watermains. Excessive pressure loss diminishes pipe performance by causing pressure losses along its length that may reduce its ability to provide its intended service. Pressure losses typically result from pipe friction due to mineral deposits and corrosion, valves that impede flow and generate energy losses, bends in the alignment of the pipe, T-connections between pipe segments, and unusually long pipe segments between the typical spacing of valve connections, defining the node to node length.

In this study, pressure loss along the length of a watermain pipe segment is calculated using the Bernoulli Equation according to the following methodology and assumptions. Water pressure is measured at pipe junctions where two or more watermain segments are connected, or valves can control flow. Hence, each pipe segment is bounded by its junctions to its neighbouring pipe segments. To simplify the calculation of the Pressure Loss, PL, the following two key assumptions are made. First, the elevation of the start and endpoints of the pipe segment is assumed to be the same. Second, the diameter of the pipe segment is assumed to remain constant along its length, and hence the water velocity remains constant. Therefore, Pressure Loss, PL $[m]$, can be calculated by using only the pressure potential component of the Bernoulli Equation, as shown in Equation 2-6.

$$PL = \mathbb{P}_{start} - \mathbb{P}_{end} \qquad \text{2-6}$$

where: $\mathbb{P}_{start}$ and $\mathbb{P}_{end}$ $[kPa]$ are the water pressures at the inflow and outflow ends of a given pipe segment, respectively. Similar to the Total Number of Breaks, the pressure loss is not normalized by the length of the pipe segment, given that the entire pipe segment length serves a single functional purpose and the objective is to place the entire length of the pipe segment into a project for either replacement or rehabilitation.

The pressure loss variable is denoted as a function of two pipe size categories demarked by being either larger than or smaller than a $600mm$ diameter. In most municipalities, water pipes larger than $600mm$ are considered as "feeder mains". Thereafter, each PL category (i.e. $PL_{\leq 600mm}$ and $PL_{>600mm}$) is divided into different bins to assign a value of V_{PL} as shown in Table 2-7. Baseline values of pressure loss across a pipe section denoting major performance issues are defined here as 34.5 $[kPa]$ (or 5 $[PSI]$) for pipes ≤ 600mm and 17 $[kPa]$ (or 2.5 $[PSI]$) for pipes >600mm. These threshold values yield maximum value for $V_{PL,1}$ and indicate that the pipe segment should be immediately prioritized for rehabilitation or replacement. The threshold values may be adjusted by specific flow monitoring and pressure control points installed by a utility provider within their specific network or further informed by hydraulic model simulations. The second bin captures the notion that most watermain pipe segments lose some pressure along their length due to pipe friction while still providing acceptable Levels of Service. However, their pressure loss denotes that they warrant attention when prioritizing future rehabilitation and replacement activity. Hence, $V_{PL,2} < V_{PL,1}$. Finally, the third bin reflects pressure losses of a new installation, resulting in $V_{PL,3} = 0$. Hence, V_{PL} is a monotonic decreasing function as PL decreases.

Table 2-7 Pressure Loss Bins

Pipe Diameter Categories	

$\boldsymbol{PL_{<600mm}}\ [\boldsymbol{kPa}]$	$\boldsymbol{PL_{>600mm}}\ [\boldsymbol{kPa}]$	$\boldsymbol{V_{PL}}\ [-]$
$PL > 34.5$	$PL > 17$	$V_{PL,1}$
$14 < PL \leq 34.5$	$10 < PL \leq 17$	$V_{PL,2}$
$PL \leq 14$	$PL \leq 10$	$V_{PL,3} = 0$

2.2.2.2 Water Quality ($\boldsymbol{WQ}$)

Water quality is an important property denoting the performance of a segment of watermain pipe, given that the water quality standards within the Province of Ontario must conform to the Clean Water Act (2006). Each municipality typically records instances of customer complaints about poor water quality, including odour, colour, and sediments. Chlorine residuals are also used to identify dead-ends and pipes that no longer conform to water quality standards. Unlined cast iron watermain pipes or pipe junctions containing lead joints are also recognized as not conforming to water quality standards. The notion that a pipe segment does or does not conform to the water quality standards is a binary decision and is denoted in Table 2-8 using two bins. Those watermain pipes that do not conform are placed in the first bin and assigned a dimensionless value of $V_{WQ,1}$. The remaining pipes that do conform are placed in the second bin and assigned a value of $V_{WQ,2} = 0$.

Table 2-8 Water Quality Bins

$\boldsymbol{WQ}\ [-]$	$\boldsymbol{V_{WQ}}\ [-]$
Does <u>not</u> conform	$V_{WQ,1}$
Does conform	$V_{WQ,2} = 0$

2.2.2.3 Conformance to Latest Standards ($\boldsymbol{CLS}$)

Performance of a watermain pipe segment based on conformance to the latest standards typically involves assessing whether the diameter of the pipe is sufficiently large to provide minimum Levels of Service to the target consumer class. For instance, each residential, commercial, institutional, and industrial consumer is required to be serviced by, at minimum, a specified pipe diameter that is stipulated by a given municipality design manual. A pipe segment that conforms to an acceptable condition but is undersized should be considered for replacement by a watermain pipe segment of larger diameter (Bennett & Glaser, 2011).

Certain pipe materials, such as lead, may not conform to current drinking water standards. Moreover, a historic capital works program may have ubiquitously installed material, such as galvanized steel pipes or substandard pipe diameters (100 mm diameter or smaller), which is now targeted by the municipalities for replacement due to changes in their design manual.

The notion that a pipe segment does or does not conform to the latest standards is a binary decision and is denoted in Table 2-9 using two bins. Those watermain pipes that do not conform are placed in the first bin and assigned a dimensionless value of $V_{CLS,1}$. The remaining pipes that do conform are placed in the second bin and assigned a value of $V_{CLS,2} = 0$.

Table 2-9 Standard Conformance Bins

$\boldsymbol{CLS}$ $[-]$	V_{CLS} $[-]$
Does not conform	$V_{CLS,1}$
Does conform	$V_{CLS,2} = 0$

2.2.3 Criticality Score (S_{C_r})

Pipe criticality measures the relative importance of the given watermain segment to provide acceptable Levels of Service to consumers and the water utility provider as a whole. Key measures of criticality are: (1) the impact of watermain failure to loss of water services for essential consumers; (2) the impact of watermain failure on the surrounding environment, and (3) the ability to effectively repair a watermain pipe promptly. Watermain pipe diameter, location, type of water service, and accessibility (depth and easements) are all variables that impact the operation and maintenance cost and the time associated with emergency watermain repairs (Al Barqawi & Zayed, 2006). For example, repairing a large diameter watermain servicing a hospital located in an environmentally sensitive area with poor accessibility is more critical than repairing a watermain of an identical diameter that is located along a local road. Each criticality property is assumed to be independent of the others and those from the Condition and Performance Scores. In the context of the Criticality Score, the three properties, $\mathcal{P}$, are: (1) pipe diameter, D; (2) pipe location, L; and (3) pipe accessibility, AC. Similar to the Condition and Performance Scores above, the contribution of each measured property on the Criticality Score is quantified by binning, $\mathcal{P}_{bin}$, into intervals, where the thresholds that bound these intervals have engineering significance based on standards or criteria relevant to each variable. The Criticality Score variable, $V_{\mathcal{P}}$, for each property is derived by applying a dimensionless weight to each bin, such that $V_{\mathcal{P}_{bin}} = f(\mathcal{P}_{bin})$. The Criticality Score, $S_{C_r} = f\left(V_{\mathcal{P}_{bin}}\right)$, for each pipe segment is a dependent variable on $V_{\mathcal{P}_{bin}}$ and is determined using Equation 2-7.

$$S_{C_r} = V_D + V_L + V_{AC} \qquad \text{2-7}$$

Consistent with the Condition and Performance Scores, bin weightings for the Criticality Score variables are constructed such that an increase in S_{Cr} denotes that the pipe segment should receive greater priority for replacement or rehabilitation.

2.2.3.1 Pipe Diameter (D)

The impact of the failure of a water pipe segment in terms of service interruptions to residential, commercial, industrial and institutional consumers, damage to the surrounding environment and infrastructure, and the time and effort required to replace or rehabilitate the pipe segment all increase with pipe diameter. Therefore, pipe diameter, D, is an important variable when considering the criticality of a pipe segment.

For brevity, the categorization of water pipe diameter is reduced into only four bins. Watermain pipes that are larger than $600\ mm$ are generally considered feeder mains (or trunk lines) and are indispensable to service an entire community. Moreover, very large watermains pipes are greater than $750\ mm$ in diameter service municipalities with large populations; hence, their relative impact is more significant than those feeder mains that service smaller communities. Watermain pipe segments with a diameter of less than $600\ mm$ diameters service progressively smaller sections of the municipality down to individual accounts. Hence, their impact on the overall Criticality Score diminishes. Therefore, $V_{D,1} > V_{D,2} > V_{D,3} > V_{D,4}$, with $V_{D,4} = 0$. The assigned bins and values are presented in Table 2-10.

Table 2-10 Pipe Diameter Bins

$\boldsymbol{D}$ $[-]$	$\boldsymbol{V_D}$ $[-]$
$D > 750\ mm$	$V_{D,1}$
$600\ mm < D \leq\ 750\ mm$	$V_{D,2}$
$300\ mm < D \leq\ 600\ mm$	$V_{D,3}$
$D \leq 300\ mm$	$V_{D,4} = 0$

2.2.3.2 Pipe Location ($\boldsymbol{L}$)

Pipe location becomes critical when high-risk environmental areas or Environmentally Significant Policy Areas (ESPAs) become impacted by break events. ESPAs are denoted on most municipalities' natural heritage maps and are recognized and protected on the premise that they provide significant municipal or natural services and ecological functions. Typical locations include watercourses such as creeks, rivers, and ponds; land subject to flooding and erosion hazards; contaminated soils; abandoned oil and gas pipelines and those currently in service; electric power corridors; major intersections, highway crossings, and railway crossings; lands containing aggregate, mineral or petroleum resources; hospitals, airports, and long-term care centres. The notion that a pipe segment is or is not located in an ESPAs is a binary decision and is denoted in Table 2-11 using two bins. Those water pipes that are in an ESPA are placed in the first bin and assigned a dimensionless value of $V_{L,1}$. The remaining pipes that are not in an ESPA are placed in the second bin and assigned a value of $V_{L,2} = 0$.

Table 2-11 Water Pipe Location Bins

$\boldsymbol{L}$ $[-]$	$\boldsymbol{V_L}$ $[-]$
Located within ESPA	V_{L1}
Located outside ESPA	$V_{L,2} = 0$

2.2.3.3 Pipe Accessibility (AC)

Pipe accessibility is a critical factor in reducing outage times during an emergency break repair. Thus, the pipe needs to have immediate and unfettered access to repair to prevent further damage and interruption of the service (Zayed & Fares, 2010). Watermain locations that have narrow or no easements, watermains that are buried deeper than normal depth, and watermains located in an area that is impassible by vehicles can create prompt emergency repair issues. The notion that a pipe segment is or is not accessible is a binary decision and is denoted in Table 2-12 using two bins. Those watermain pipes that are not accessible are placed in the first bin and assigned a dimensionless value of $V_{AC,1}$. The remaining pipes that are accessible are placed in the second bin and assigned a value of $V_{AC,2} = 0$.

Table 2-12 Accessibility Bins

$\boldsymbol{AC}$ $[-]$	$\boldsymbol{V_{AC}}$ $[-]$
Not accessible	$V_{AC,1}$
Accessible	$V_{AC,2} = 0$

2.2.4 PAN Weighting Factors ($\boldsymbol{W_C}$, $\boldsymbol{W_P}$ $\boldsymbol{and}$ $\boldsymbol{W_{C_r}}$)

Table 2-1 indicates that most of the literature involved in prioritizing watermain pipe segments for rehabilitation or replacement focuses on pipe conditions under the premise that each pipe segment in the network has sufficient performance to provide specific Levels of Service. Therefore, it can be inferred that a given watermain pipe's performance is relatively more important than its condition. For instance, if a given pipe segment is in good condition but exhibits poor performance because it does not conform to the latest standard, there is a need to mitigate the performance issue to maintain the same Level of Service. Criticality is the least important attribute relative to performance and condition to prioritize a specific pipe segment rehabilitation or replacement. For instance, a watermain pipe segment that exhibits poor condition must be maintained regardless of its location and criticality. However, of the set of pipe segments exhibiting poor conditions, those that provide service to critical locations are given priority relative to others in the same set. The idea of relative importance is conveyed through the weighting factors for Condition, Performance and Criticality as $W_P > W_C > W_{Cr}$.

This study assumed that all variables are independent and do not correlate with one another.

2.3 Application of the Priority Action Number (*PAN*)

To demonstrate the application of the PAN for quantifying the condition, performance and criticality of a pipe segment, and thereafter ranking the pipe as part of a capital works project for replacement and/or rehabilitation, two scenarios are developed to enumerate all property bin values, $V_{\mathcal{P}_{bin}}$, and weight factors, W_P, W_C and W_{Cr} to determine the PAN. All assigned bin values and weight factors are scaled between 0 to 15, with 0 being the least important and 15 being the most important. This scale is an assumption for consistency among all variable values. The scale may change but needs to stay consistent for all variable values.

Scenario A consists of a 50 m long, 400 mm in diameter ductile iron (DI) watermain pipe segment that services a hospital. The DI pipe was installed in 1980 within corrosive soil and crosses a creek and wetland that is not accessible. The pipe segment has an expected 70 years of service life and has experienced eleven breaks, with nine breaks occurring within the last five years. The pressure loss is 48.6 [kPa]. The operation and maintenance cost (OpEx) is $\$25/m/yr$ and replacement cost (CapEx) is $\$1{,}500/m$.

Scenario B consists of a 50 m long, 400 mm in diameter concrete (CONC) watermain pipe segment that services a hospital. The concrete pipe segment was installed in 1980 within non-corrosive soil and expected 70 years of service life. The pipe segment crosses a creek and wetland but is accessible via an access road. Since installation, the pipe segment has experienced a total of eleven breaks, with nine breaks occurring with the last five years. The pressure loss is 13.8 [kPa]. The operation and maintenance cost (OpEx) is $\$25/m/yr$ and replacement cost (CapEx) is $\$1{,}500/m$.

2.3.1 Condition Score (S_C) determination

Scenario A:

The Remaining Service Life can be calculated using Equation 2-3.

$$\boldsymbol{RSL = [Expected\ Life - (\mathcal{R}_M * Expected\ Life)] - Age\_in\_Service}$$

For this scenario, the $Expected\ Life$ = 70 years and the $Age\_in\_Service$ = 2020-1980 = 40 years. Since the AC pipe segment is placed in corrosive soil Table 2-2 determines $\mathcal{R}_M$ = 0.5. Thus, the $RSL\ = [70\ -\ (0.5 * 70)] -\ 40\ =\ -5\ years$ which means it is 5 years past its service life. Table 2-13 with $RSL \leq 15$ years gives $V_{RSL,1} = 15$. The negative service life would fit in the RSL< 15 bin which has the highest variable value.

Table 2-13 Bin Values for Remaining Service Life Assumed.

$RSL\ [years]$	$V_{RSL}\ [-]$
$RSL \leq 15\ years$	$V_{RSL,1} = 15$
$15 < RSL \leq 30\ years$	$V_{RSL,2} = 10$
$30 < RSL \leq 50\ years$	$V_{RSL,3} = 5$
$RSL > 50\ years$	$V_{RSL,4} = 0$

The Total Number of Breaks since installation is 11, so $TB\ = 11$. Table 2-14 with TB ≥9 gives $V_{TB,1} = 15$.

Table 2-14 Bin Values for Total Number of Breaks.

$TB\ [-]$	$V_{TB}\ [-]$
$TB \geq 9$	$V_{TB,1} = 15$
$8 \geq TB \geq 5$	$V_{TB,2} = 10$
$4 \geq TB \geq 1$	$V_{TB,3} = 5$
$TB = 0$	$V_{TB,4} = 0$

The number of watermain breaks within the last five years is nine so $TB_{5yrs} = 9$. Table 2-15 with $TB_{5yrs} \geq 5$ gives $V_{TB_{5yrs},1} = 15$.

Table 2-15 Bin Values for Number of Breaks within the Last Five Years.

$TB_{5yrs}\ [per\ year]$	$V_{TB_{5yrs}}\ [-]$
$TB_{5yrs} \geq 5$	$V_{TB_{5yrs},1} = 15$
$4 \geq TB_{5yrs} \geq 3$	$V_{TB_{5yrs},2} = 10$
$2 \geq TB_{5yrs} \geq 1$	$V_{TB_{5yrs},3} = 5$

$TB_{5yrs} = 0$	$V_{TB_{5yrs},4} = 0$

The Maintenance Index is calculated using Equation 2-4.

$MI\ = (OpEx \times RSL)/CapEx$ = (25 × -5)/1500 = -0.083

where $OpEx$ = $\$25/m/yr$, RSL = -5 and $CapEx$ = $\$1{,}500/m$

Since $MI = -0.083$, all negative MI is considered as a higher priority because pipe passed its service life. Therefore regardless of the value, it would fit into the highest bin $V_{MI,3} = 15$.

Table 2-16 Bin Values for Maintenance Index

MI [−]	V_{MI} [−]
$MI \leq 0.01$	$V_{MI,1} = 0$
$0.01 < MI \leq 0.05$	$V_{MI,2} = 10$
$MI > 0.05$	$V_{MI,3} = 15$

The Condition Score is determined using Equation 2-2:

$S_{CA} = V_{RSL} + V_{TB} + V_{TB_{5yrs}} + V_{MI} = 15 + 15 + 15 + 15 = 60$

Given that all four properties that comprise the Condition Score are enumerated on the interval of 0 to 15, the maximum S_C would be 60. If a Condition Score between 30 to 60 is deemed to be "High" and less than 30 is deemed to be "Low" a $S_{C_A} = 60$ indicates that pipe Segment A has a high condition score and therefore is a high priority for replacement and/or rehabilitation.

Scenario B:

Following the same method as for Scenario A, the Condition Score is determined for Scenario B.

First, the Remaining Service Life, RSL, is determined using Equation 2-3.

RSL = [70 – (0.0 x 70)] - 40 = 30 years

where the $Expected\ Life$ = 70 years and the $Age\_in\_Service$ = 2020-1980 = 40 years and $\mathcal{R}_M$ = 0.0 since the pipe segment is placed in non-corrosive soil. Thus, there is no reduction to the pipe's expected life.

Using Table 2-13 $15 < RSL \leq 30\ years$ gives $V_{RSL,2} = 10$.

Total Number Breaks and breaks in the last five years are the same as the pipe in Scenario A, therefore, $V_{TB_{5yrs},1} = 15$.

The Maintenance Index calculated using Equation 2-4

$MI\ = (OpEx \times RSL\ )/CapEx$ = (25 ×30)/1500 = 0.5

where $OpEx$ = \$$25/m/yr$, RSL = 30 yr and $CapEx$ = \$$1{,}500/m$

For $MI > 0.05$ Table 2-16 gives $V_{MI,3} = 15$.

The Condition Score is calculated using Equation 2-2.

$$S_{CB} = V_{RSL} + V_{TB} + V_{TB_{5yrs}} + V_{MI} = 10 + 15 + 15 + 15 = 55$$

Using 30 to 60 Condition Score to be "High" and less than 30 is deemed to be "Low" a $S_{C_A} = 40$ indicates that pipe Segment B has a high condition score is a high priority for replacement and/or rehabilitation. Since $S_{C_A} = 60\ >\ S_{CB} = 55$ the pipe in scenario A will have a higher priority than the pipe in scenario B.

2.3.2 Performance Score (S_P) Calculation

Scenario A:

The pressure loss along the pipe segment is given as 48.6 kPa. Using Table 2-17 $PL > 34.5$ for a 400mm diameter pipe gives $V_{PL_1} = 15$.

Table 2-17 Bin Values for Pressure Loss [kPa]

Pipe Diameter Categories	

$PL_{<600mm}$ $[kPa]$	$PL_{>600mm}$ $[kPa]$	V_{PL} $[-]$
$PL > 34.5$	$PL > 17$	$V_{PL,1} = 15$
$14 < PL \leq 34.5$	$10 < PL \leq 17$	$V_{PL,2} = 5$
$PL \leq 14$	$PL \leq 10$	$V_{PL,3} = 0$

There is no information on recorded water quality complaints, so it is assumed that the Water Quality does conform. Using Table 2-18 $V_{WQ,2} = 0$ for a pipe the conforms to Water Quality

Table 2-18 Assumed Bin Values for Water Quality

WQ $[-]$	V_{WQ} $[-]$
Does not conform	$V_{WQ,1} = 15$
Does conform	$V_{WQ,2} = 0$

With respect to Standard Conformance, no information is provided to indicate that no conformance to Standards. Thus, using Table 2-19, the bin values for standard conformance gives $V_{CLS,2} = 0$.

Table 2-19 Assumed Standard Conformance Bin Values

CLS $[-]$	V_{CLS} $[-]$
Does not conform	$V_{CLS,1} = 15$
Does conform	$V_{CLS,2} = 0$

The Performance Score for the pipe in Scenario A is calculated using Equation 2-5.

$$S_{PA} = V_{PL} + V_{WQ} + V_{CLS} = 15 + 0 + 0 = 15$$

The highest Performance Score using a maximum value of 15 will be 45. If a Performance Score between 22.5 to 45 denotes "High" and less than 22.5 is "Low" as $S_{P_A} = 15$ is considered to be "Low". This low Performance Score indicates that pipe Segment A has no performance issues at this time.

Scenario B:

Following the same procedure as Scenario A, the Performance Score for pipe Segment B is determined.

The Pressure-loss is given as 13.8 kPa. Thus, using Table 2-17 $PL \leq 14$ and 400mm diameter pipe gives $V_{PL_3} = 0$.

There are no water quality complaints therefore $V_{WQ,2} = 0$. There is also no indication that it does not conform to Standards therefore $V_{CLS,2} = 0$.

The Performance Score for the pipe in Scenario B is calculated using Equation 2-5.

$S_{PB} = V_{PL} + V_{WQ} + V_{CLS} = 0 + 0 + 0 = 0$

Using the same methodology assumed for the pipe in Scenario A, $S_P = 0$ indicates a "Low" Performance Score and that the pipe has no performance issues.

2.3.3 Criticality Score (S_{C_r}) Calculation

Scenario A:

The watermain pipe diameter, D is 400mm. Using Table 2-20 $V_{D,3} = 5$ for $300\ mm < D \leq\ 600\ mm$ diameter pipes.

Table 2-20 Assumed Bin Values for Pipe Diameter

$\boldsymbol{D}$ [−]	$\boldsymbol{V_D}$ [−]
$D > 750\ mm$	$V_{D,1} = 15$
$600\ mm < D \leq\ 750\ mm$	$V_{D,2} = 10$
$300\ mm < D \leq\ 600\ mm$	$V_{D,3} = 5$
$D \leq 300\ mm$	$V_{D,4} = 0$

The pipe crosses a creek within an environmentally sensitive area. Using Table 2-21 $V_{L,1} = 15$ pipe as it is within the ESPA area.

Table 2-21 Assumed Bin Values for Water Pipe Location

$\boldsymbol{L}$ [−]	$\boldsymbol{V_L}$ [−]
Located within ESPA	$V_{L,1} = 15$
Located outside ESPA	$V_{L,2} = 0$

Since the pipe is not accessible, Table 2-22 assigns $V_{AC,1} = 15$.

Table 2-22 Assumed values for Accessibility Bins

$\boldsymbol{AC}$ [−]	$\boldsymbol{V_{AC}}$ [−]
Not accessible	$V_{AC,1} = 15$
Accessible	$V_{AC,2} = 0$

The Criticality Score for the pipe in Scenario A is calculated using Equation 2-7.

$$S_{C_r} = V_D + V_L + V_{AC} = 5 + 15 + 15 = 35$$

Scores between 22.5 to 45 are deemed to be "High" and less than 22.5 to be "Low". As with S_C and S_P, the "High" category and higher Criticality Score denotes a higher case for priority. Accordingly, $S_{C_{r_A}} = 35$ indicates that this particular pipe segment is considered critical and has a "High" Criticality Score.

Scenario B:

The diameter of the pipe is 400mm in Scenario B and the same as for Scenario A. Hence $V_{D,3} = 5$.

The pipe also crosses a creek within an environmentally sensitive area, thus $V_{L,1} = 15$. The pipe is accessible therefore $V_{AC,0} = 0$.

The Criticality Score for the pipe in Scenario B is calculated using Equation 2-7.

$$S_{C_{rB}} = V_D + V_L + V_{AC} = 5 + 15 + 0 = 20$$

The $S_{C_{rB}} = 20$ will be "Low" and indicates this particular pipe segment is not critical. Since $S_{C_{r_A}} > S_{C_{r_B}}$ Scenario A is more critical than Scenario B.

2.3.4 PAN Calculation

The PAN is calculated using Equation 2-1

$$PAN = S_C\, W_C + S_P\, W_P + S_{C_r} W_{Cr}$$

where the Condition, Performance and Criticality Scores multiplied by their respective weighting factors with $W_P > W_C > W_{Cr}$.The weight factors for this analysis are assigned as $W_C = 8$; $W_P = 10$; and, $W_{C_r} = 6$ using a scale of 0 to 15.

The resulting PAN for Scenario A and B pipe segments are determined as

$$PAN_{Scenario\ A} = 60 \times 8 + 15 \times 10 + 35 \times 6 = 840$$

$$PAN_{Scenario\ B} = 55 \times 8 + 0 \times 10 + 20 \times 6 = 560$$

Using maximum scores $PAN_{max} = 1200$. For this analysis "High" is 1200 ≥ PAN ≥ 800, "Medium" is 800 > PAN > 400, and "Low" is 400 ≥ PAN ≥ 0. Scenario, A PAN of 840 is "High" while Scenario B PAN of 560 is "Medium" using these PAN categories. Thus, Scenario A has a higher priority for replacement and/or rehabilitation than pipe Segment B.

2.3.5 Mitigation Technology

Table 2-23 provides an example of potential mitigation classification outcomes that are differentiated based on abstract boundaries denoted by "Low", "Medium," and "High" Scores and for the PAN, Condition, Performance and Criticality Scores.

Table 2-23 Potential Mitigation Solutions based on Condition, Performance, Criticality Scores, and PAN

Mitigation Strategy	Condition Score	Performance Score	Criticality Score	PAN	Mitigation Technology
1	High	High	High	High	Up-Size
2	High	High	Low	High	Up-Size
3	High	Low	High	High	Replace
4	High	Low	Low	Medium	Repair
5	Low	High	High	High	Up-Size
6	Low	High	Low	Low	Do Nothing
7	Low	Low	High	Low	Do Nothing

8	Low	Low	Low	Low	Do Nothing

Using Table 2-23 Scenario A pipe has "High" Condition Score, "Low" Performance Score, "High" Criticality Score, and "High" PAN falls into the mitigation Strategy 3 Replace". Scenario B pipe has "High" Condition Score, "Low" Performance Score, "Low" Criticality Score and "Medium" PAN falls into Mitigation Strategy 4 Repair.

2.4 Conclusions

In this study, a Priority Action Number (PAN) is proposed and developed to score and rank pipe segments to prioritize them for replacement and rehabilitation. The PAN develops a standardized set of rules that allow for defensible, repeatable and auditable prioritization decisions that can be automated in computer programs and implemented into ArcGIS.

The PAN consists of determining the summation of condition, performance and criticality score multiplied by each score appropriate assigned weight. Each score is considered independent, and weighting factors for Condition, Performance and Criticality are set as $W_P > W_C > W_{Cr}$. Each Score is developed so that a higher Score and thus higher PAN means pipe segment higher priority for replacement and/or rehabilitation.

Two pipe segment Scenarios are presented to demonstrate the PAN calculation methodology, and an example of a pipe mitigation matrix is shown to demonstrate how the PAN Scores and be used to develop repeatable, defensible and audible pipe segments prioritization decisions.

Further work is required to establish appropriate weights for Scores and rationale and an industry-applicable pipe segment decision matrix.

Chapter 3

An Expert Opinion Algorithm for Prioritizing and Mitigating Watermain Networks: Model Development

Abstract

MWN is a significant fundamental system used in delivering potable water. Due to the deterioration of MWN that results in the structural and hydraulic capacity reduction of these systems, municipalities are faced with obstacles in defining the process of deterioration and the factors affecting the deterioration rate. The municipalities then prioritize the maintenance of their infrastructure under this circumstance with optimum use of resources. This chapter presents and develops a prioritizing approach for the watermain networks' capital activities and aids in selecting assistive technology for rehabilitation and renewal. Using the MWN comprehensive database that is mapped in an ArcGIS system, a machine learning classifier model is proposed to classify all pipes in MWN and assign a capital work activity to all pipes in MWN. Through the NBC supervised learning algorithm, the capital project decision-making process is automated.

Keywords: artificial intelligence, machine learning algorithm, Naïve Bayes Classifier, watermain Capital Activities, Prioritization, Water network, supervised machine learning algorithm, an engineer assigned variable values, expert's assigned variable values, prior distributions, posterior distributions, and decision making

3.1 Introduction

Watermain Networks are deteriorating and ageing over time. Deterioration reduces the hydraulic and structural capacity of the water distribution networks. All over the world, metropolises are faced with the challenges of recognizing the factors that can affect the rate of water pipes deterioration. To address these challenges, municipalities need to define technologies and methodologies for Water network rehabilitation, assessment, management, construction, design, and planning that consider the social, environmental, and economic factors. This chapter outlines models that prioritize and mitigates Watermain networks and assist in the recovery of Artificial Intelligence (AI). It builds on expert opinions to develop a relatively standard method of managing water networks and replicate expert opinions using AI.

Key findings demonstrate a comprehensive database preparation and a method to capture engineering decisions and propose a machine learning algorithm that is capable of replicating expert opinions on planning capital activities is needed. The capital activities of water pipe are based on the current condition, performance and criticality of every pipe within the water system (Halfawy & Hengmeechai, 2014). Two analysis methods have been undertaken to ensure that the correct data is obtained upon completing this study. These include surveys and supervised machine learning algorithms and applications to prioritize water pipes condition, performance and criticality, and a mitigating maintenance solution for every pipe through the water system.

3.1.1 Background

Unlike wastewater infrastructure, water systems do not have a standardized method to measure and rank their condition or having a certain solution for a defect (NRC.CNRC, 2003). Each municipality has a different way of managing its drinking water infrastructure, and each expert has different opinions. There is no standard way, even within the same organization to date, to assess all water pipes and plan water capital activities (NRC, CNRC, 2005). American Society for Civil Engineers reported in 2013 a $3.6 trillion investment need by 2020 to replace ageing infrastructure in North America (ASCE, 2013). Combining expert opinion and machine learning methodologies is a relatively new technology in the engineering industry (Iqbal & Yan, 2015). There are new areas such as automated bridge and roadway inspection using machine learning algorithms recently (Tagh Bostani, 2015); (Ravikumar et al., 2011). These efforts focused on automating visual inspection using a support vector machine to classify road or bridge defect patterns.

Machine learning models are used primarily in other civil engineering fields thus far rather than complex water pipe networks. Halfawy & Hengmeechai (2014) advises using automated deficiency detection tools for sanitary sewer inspection pattern recognition algorithms to classify pipe defects captured by CCTV inspection videos. A set of histograms of oriented gradients features extracted from positive and negative examples of the defect are used as classifiers to train the algorithm. Yang & Su (2008), used three neural network approaches, back-propagation neural network, radial basis network, and support vector machine to classify sewer pipe defect patterns. For this research, CCTV inspection is used as an expert opinion. The learning algorithm is yet to be used in a water pipe to classify defects and propose a mitigation methodology.

The machine-learning algorithm has been used rarely as a decision-making tool in the water industry. Kumar et al. (2018) used a machine-learning algorithm to predict the risk of failure on water infrastructure. The model considered limited pipe physical condition properties as variables in the machine learning model. Kabir et al. (2015) used Bayesian Model Averaging method to predict pipe failure. The influential pipe-dependent and time-dependent covariates are used to develop the survival curves and predict the water pipe failure rates. Asnaashari et al. (2013) used the Artificial Neural Network method to prioritize Watermain repair and replacement activities. Eight independent pipe physical properties are employed as variables influencing the water pipe failure rate. Al Barqawi & Zayed (2006) proposed another Artificial Neural Network approach on condition rating model to prioritize water pipe rehabilitation. Water pipe physical, environmental, and operational factors are considered on limited water pipe materials. Table 3-1 summarizes linear machine learning models. A comprehensive machine learning algorithm model, which includes condition, performance, and criticality variables and automates capital project decisions, is yet to be proposed.

Neglecting ageing infrastructure, especially in older cities; where large portions of the water infrastructure were laid more than a century ago and have passed their operating life, such as the Cty of Toronto; can cause massive property damage by flooding homes and businesses, creating large sinkholes that destroy roads and vehicles on those roads, lead to leaks into gas lines preventing homes from receiving heat, and destroy power lines preventing homes from receiving power (Jerome, 2017).

Table 3-1 Literature Review Summary

Machine Learning Models	***Water Network Study***	***Research Fields***	***Condition***	***Performance***	***Criticality***	***Mitigation Technology***
Caradot et al. 2018	No	Sanitary Sewer Pipe Deterioration Model	×	×	×	×
Tagh Bostani, 2015	No	Prioritizing and Ranking Bridge Rehabilitation	✓	×	×	✓
Sousa et al., 2014	No	Classifying Sanitary Sewer Condition	✓	×	×	×
Halfawy & Hengmeechai, 2014	No	Automate Sanitary Sewer Pipe Deficiency Ranking	✓	×	×	×
Harvey, & McBean 2013	No	Prioritizing Sanitary Sewer Inspection	✓	×	×	×

Ravikumar et al., 2011	No	Prioritizing Road Way Rehabilitation	✓	✗	✗	✓
Yang & Su, 2008	No	Classify Sanitary Sewer Pipe Defect Patterns	✓	✗	✗	✗
Kumar et al. 2018	Yes	Classify the Risk of Watermain Breakage	✓	✗	✗	✗
Ahmadi et al., 2015	Yes	Prioritizing Water Pipe inspection	✓	✗	✗	✗
Kabir et al., 2015	Yes	Predicting the Water Pipe Failure	✓	✗	✗	✗
Asnaashari et al., 2013	Yes	Prioritizing Water Pipe Repair and Rehabilitation	✓	✗	✗	✓
Al Barqawi & Zayed, 2006	Yes	Classify Water Pipe Condition Rating	✓	✓	✓	✗

With the onset of ageing water infrastructure, limited available resources to maintain the same Level of Service (LOS) are an onerous responsibility (NRC, CNRC, 2007). By automating capital activity decision-making processes, not only consistency and defence-ability would be added to capital activities decisions, but also the resources can be spending on much-needed water asset maintenance activities.

While expert opinions are subjective, it's required to be supported by consistent decision-making models (Aven, 2016). Prioritizing watermain capital activities, a complete modelling approach is needed and yet to be proposed. This study's results may provide a baseline that could potentially be used to benchmark the watermain performance measurement at different levels of municipal organizations. The proposed method automates and replicates expert opinion. Classifier models with machine learning are inspired by various disciplines, including computer science, medical, and other engineering fields. Machine learning to the author's knowledge has not been applied to prioritize capital works activities for a municipal water pipe network. The core function of Machine Learning attempts to determine a good predictor using available data to automatically classify the output (Iqbal & Yan, 2015). Classification is the process of using a model to predict unknown values using several known values. The database with all known variables is called a training database that is used to develop the Naïve Bayes Classifier (NBC) model.

In summary, past studies confirm that due to several complexities, uncertainties, and imperfection of the water network and its available data, there is a need for a comprehensive multi-criteria database to prioritize pipe maintenance decisions based on engineering expert judgment. An automated machine learning model for consistent raking of existing water pipe condition, performance, and criticality of all water pipes through MWN is required to automate the capital activities decision-making process.

3.1.2 Methodology

This chapter's main objective is to build supervised machine learning models on rehabilitation and replacement of water infrastructure to replicate engineering judgment for linear water infrastructure's capital activities. This study proposes a decision support tool that will add consistency and defence-ability to the water pipes capital program. This study would save municipalities much-needed resources by automating the screening process by categorizing data to classified score systems assigned by professionals. The learning algorithm will repeat engineering decisions automatically. This chapter will explain the machine learning methodology to rank the entire water system with multi-objective mitigation scenarios.

This research introduces two models to prioritize water pipes based on their condition, performance, and criticality properties and mitigating capital project decisions based on expert's opinions. The outcome of these models are classifying all water pipes within the MWN for condition and performance into five prioritizing classes as (very poor, poor, moderate, good, and very good) and criticality of water pipes in five classes as (very high, moderately high, medium, moderately low and very low); mitigating capital activities in four different classes as (do nothing, rehab and renovate using trenchless technology, replace with the same pipe size, upsize or replace with larger size pipe). This chapter introduces the NBC model with a supervised learning algorithm. The proposed model will be trained using engineering judgment and expert opinion and can replicate the same decisions.

Figure 3-1 summarizes the NBC model in a flow chart. NBC requires having prior, posterior, and likelihood distributions. The prior and posterior classes are calculated from separate information for the same water pipes within the MWN. Variable values to calculate prior and posterior classes are gathered from two different sources. The left part of the Figure 3-1 shows prior classes are calculated using initial assigned variable values by a municipal engineer. The right part of the Figure 3-1 shows posterior classes or target classes are calculated using the survey results by asking professional engineers who are considered experts in the municipal water industry. Class boundaries are set based on the minimum and maximum scores calculated for all pipes within the database. The supervised machine learning algorithm calculates the likelihood distributions to develop the decision tree rules and weights where it replicates the information contained within the likelihood distribution.

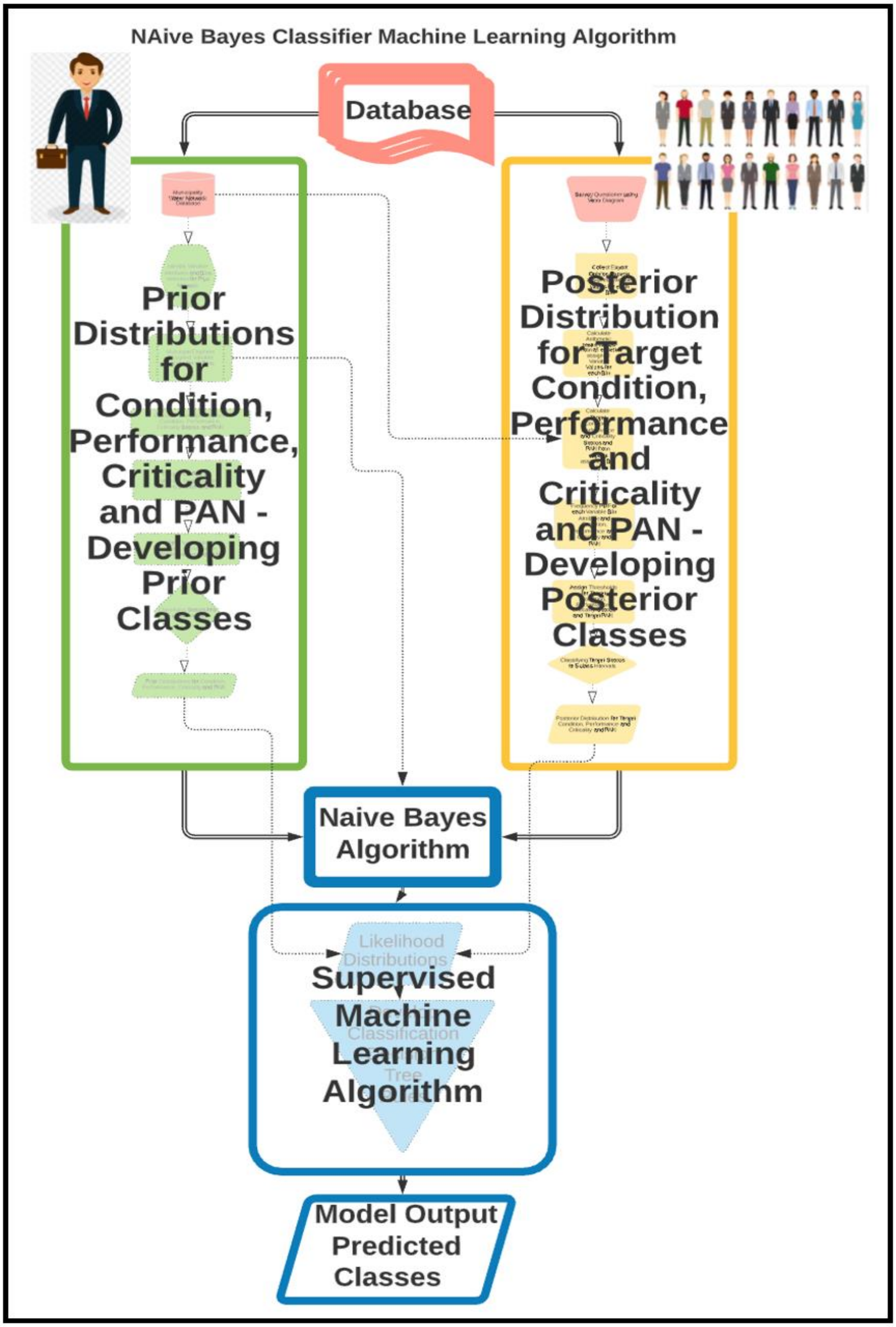

Figure 3-1 Naïve Bayes Classifier Flow Chart

The proposed model is organized into two levels. The first is a prioritization model that classifies each pipe within the MWN into five classes for condition, performance and criticality based on expert opinion. The second is a mitigation model that assigns a capital plan activity to each pipe within MWN is based on expert judgement. The following sections explain the database and two-level model development. The model is downloaded from NumPy and SciPy library and prepared in Python scripting language available in GIS.

3.2 Data and Variables

According to recommended best practice 2005, all North American Municipalities are obligated to store their water assets information in ArcGIS format. The stored ArcGIS shapefile water database is called the MWN. This database included but is not limited to all water pipe attributes required properties for the proposed NBC models. These databases are included water pipe information such as diameter, the total number of breaks, soil conditions, location, and location or accessibility. Some water pipe information is not time-dependent that will not change over time. But there is time-dependent information; for example, pipe diameter and material will not change, but the Remaining Service Life and number of breaks may change over time. This information is collected as a set of attributes X, and with each attribute being assigned a variable value V_{Xi} by being categorized into one of several bins i with set boundaries. All bin thresholds and boundaries are described in detail in Chapter 2. Table 3-2 summarizes the list of variables considered in Condition, Performance and Criticality classifiers.

Table 3-2 List of Variables Considered for Condition, Performance and Criticality

Condition Variables (S_C)		Performance Variables (S_P)		Criticality Variables (S_{C_r})	
Remaining Service Life	V_{RSL_i}	Water pressure loss	V_{PL_i}	Pipe diameter	V_{D_i}
Total number of breaks	V_{TB_i}	Water quality	V_{WQ_i}	Pipe location	V_{L_i}
Total number of breaks within the last five years	$V_{TB_{5yrs_i}}$	Conformance to latest standards	V_{CLS_i}	Pipe accessibility	V_{AC_i}
Maintenance index	V_{MI_i}				

Scores are the sum of all variable values. The equation for Condition Score S_C, Performance Score S_P, and Criticality Score S_{Cr}, is repeated from Chapter 2 as:

$$S_C = V_{RSL} + V_{TB} + V_{BLFVY} + V_{MI} \tag{3-1}$$

$$S_P = V_{HL} + V_{WQ} + V_{CLS} \tag{3-2}$$

$$S_{C_r} = V_D + V_L + V_{Ac} \tag{3-3}$$

$$PAN = S_C\, W_C + S_P\, W_P + \ S_{C_r} W_{Cr} \tag{3-4}$$

Municipal engineers working for municipalities are responsible for reviewing and keep MWN up-to-date. Municipal engineers are also responsible for capital activities according to information available in the MWN database for pipe condition, performance, and criticality. Based on engineering judgment, each municipal engineer follows different criteria for planning and prioritizing capital activities within a different municipality to keep the LOS. There is no standardized method among all municipalities for planning and prioritizing capital activities. The goal of this effort is to produce a model predicted classification of watermain that standardize and prioritize capital activities for water pipes to keep the same LOS among all municipalities based on expert judgment

NBC algorithm is well suited for the extensive database with many data points, such as the MWN database. MWN is a water pipe inventory, and each pipe is considered a data point in the database. The MWN database includes all variable measuring conditions, performance, and criticality explained in Chapter 2. Variables could be continuous, categorical, or binary. Variable collection and boundaries are done by a municipal engineer initially, as described in Chapter 2. The expert opinion may deviate from the municipal engineer's decision. Since the municipal engineer judgement is aggregated to local MWN and expert opinion is mainly aligned with general industry best practice. For instance, one MWN maybe consist of pipes, which are all relatively short Remaining Service Life, but not all pipes with low Remaining Service Life would be classified the same, especially compared to the networks that the “experts” deal with. Hence, prioritizing pipes in the MWN based on their excessive age is not informative.

To benchmark the variable values and boundaries, a survey questioner is prepared and asked professional engineers experts in the water industry to evaluate the variables, assign variable values and boundaries to all selected attributes. As shown in Table 3-3, each data point represents a water pipe in the MWN database; every pipe have all variable values assigned by the Municipal engineer V_{X_i} and assigned by expert $\bar{V}_{X_i}$. Each water pipe fits into one bin for each variable with one variable value that is assigned a municipal engineer and one bin with one variable value that is accredited by expert opinion. Therefore, each pipe within the MWN has one score $S_C, S_P, and\ S_{C_r}$ and PAN computed from municipal engineer assign variable values and one Target Score $\bar{S}_C, \bar{S}_P, \bar{S}_{Cr}\ and\ \overline{PAN}$ calculated from expert’s assigned variable values for condition, performance, and criticality.

Table 3-3 Supervised Learning Data Organization

	Municipal Engineer Assigned					Expert Assigned (Target)					Model Predicted				
Data Point / Attributes	Pipe 1	Pipe 2	…	…	Pipe n	Pipe 1	Pipe 2	…	…	Pipe n	Pipe 1	Pipe 2	…	…	Pipe n
Variable 1 - (RSL)	$V_{RSL_i,1}$	$V_{RSL_i,2}$	…	…	$V_{RSL_i,n}$	$\bar{V}_{RSL_i,1}$	$\bar{V}_{RSL_i,2}$	…	…	$\bar{V}_{RSL_i,n}$	NA	NA	…	…	NA
Variable 2 - TB	$V_{TB_i,1}$	$V_{TB_i,2}$	…	…	$V_{TB_i,n}$	$\bar{V}_{TB_i,1}$	$\bar{V}_{TB_i,2}$	…	…	$\bar{V}_{TB_i,n}$	NA	NA	…	…	NA
Variable Value 3 - BLFVY	$V_{BLFVY_i,1}$	$V_{BLFVY_i,2}$	…	…	$V_{BLFVY_i,n}$	$\bar{V}_{BLFVY_i,1}$	$\bar{V}_{BLFVY_i,2}$	…	…	$\bar{V}_{BLFVY_i,n}$	NA	NA	…	…	NA
Variable Value 4 - X	$V_{X_i,1}$	$V_{X_i,2}$	…	…	$V_{X_i,n}$	$\bar{V}_{X_i,1}$	$\bar{V}_{X_i,2}$	…	…	$\bar{V}_{X_i,n}$	NA	NA	…	…	NA
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
Variable Value 10 - AC	$V_{AC_i,1}$	$V_{AC_i,2}$	…	…	$V_{AC_i,n}$	$\bar{V}_{AC_i,1}$	$\bar{V}_{AC_i,2}$	…	…	$\bar{V}_{AC_i,n}$	NA	NA	…	…	NA
Condition Score	S_{C_1}	S_{C_2}	…	…	S_{C_n}	$\bar{S}_{C_1}$	$\bar{S}_{C_2}$	…	…	$\bar{S}_{C_n}$	NA	NA	…	…	NA
Performance Score	$S_{P,1}$	S_{P_2}	…	…	S_{P_n}	$\bar{S}_{P_1}$	$\bar{S}_{P_2}$	…	…	$\bar{S}_{P_n}$	NA	NA	…	…	NA
Criticality Score	$S_{C_{r_1}}$	$S_{C_{r_2}}$	…	…	$S_{C_{r_n}}$	$\bar{S}_{C_{r_1}}$	$\bar{S}_{C_{r_2}}$	…	…	$\bar{S}_{C_{r_n}}$	NA	NA	…	…	NA
Condition Class	$\mathbb{C}_{C_j,1}$	$\mathbb{C}_{C_j,2}$	…	…	$\mathbb{C}_{C_j,n}$	$\bar{\mathbb{C}}_{C_j,1}$	$\bar{\mathbb{C}}_{C_j,2}$	…	…	$\bar{\mathbb{C}}_{C_j,n}$	$\bar{\bar{\mathbb{C}}}_{C_j,1}$	$\bar{\bar{\mathbb{C}}}_{C_j,2}$	…	…	$\bar{\bar{\mathbb{C}}}_{C_j,n}$
Performance Class	$\mathbb{C}_{P_j.1}$	$\mathbb{C}_{P_j.2}$	…	…	$\mathbb{C}_{P_j,n}$	$\bar{\mathbb{C}}_{P_j,1}$	$\bar{\mathbb{C}}_{P_j.2}$	…	…	$\bar{\mathbb{C}}_{P_j,n}$	$\bar{\bar{\mathbb{C}}}_{P_j,1}$	$\bar{\bar{\mathbb{C}}}_{P_j,2}$	…	…	$\bar{\bar{\mathbb{C}}}_{P_j,n}$
Criticality Class	$\mathbb{C}_{Cr_j,1}$	$\mathbb{C}_{Cr_j,2}$	…	…	$\mathbb{C}_{Cr_j,n}$	$\bar{\mathbb{C}}_{Cr_j,1}$	$\bar{\mathbb{C}}_{Cr_j,2}$	…	…	$\bar{\mathbb{C}}_{Cr_j,n}$	$\bar{\bar{\mathbb{C}}}_{C_{r_j},1}$	$\bar{\bar{\mathbb{C}}}_{Cr_j,2}$	…	…	$\bar{\bar{\mathbb{C}}}_{Cr_j.n}$
Weights	W_C, W_P, W_{C_r}					$\bar{W}_C, \bar{W}_P, \bar{W}_{C_r}$					$\bar{\bar{W}}_{RSL}, \bar{\bar{W}}_{TB}, \bar{\bar{W}}_{BLFVY}, \ldots.., \bar{\bar{W}}_{AC}$				
PAN	PAN_1	PAN_2	…	…	PAN_n	$\overline{PAN}_1$	$\overline{PAN}_2$	…	…	$\overline{PAN}_n$	NA	NA	…	…	NA
Mitigation Class	$\mathbb{C}_{PAN_j,1}$	$\mathbb{C}_{PAN_j,2}$	…	…	$\mathbb{C}_{PAN_j,n}$	$\bar{\mathbb{C}}_{PAN_j,1}$	$\bar{\mathbb{C}}_{PAN_j,2}$	…	…	$\bar{\mathbb{C}}_{PAN_j,n}$	$\bar{\bar{\mathbb{C}}}_{PAN_j,1}$	$\bar{\bar{\mathbb{C}}}_{PAN_j,2}$	…	…	$\bar{\bar{\mathbb{C}}}_{PAN_j,n}$

As it shows in Table 3-3, each pipe within the MWN have condition, performance and criticality and mitigation classifiers $\mathbb{C}_{C_j} \in \{Very\ Poor, Poor, Fair, Good, Very\ Good\}$ and $\mathbb{C}_{PAN} \in \{Do\ Nothing, Rehabilitation, Replacemen, Upsize\}$) that are assigned by a municipal engineer $\mathbb{C}_{C_j}, \mathbb{C}_{P_j}, \mathbb{C}_{C_{r_j}} and\ \mathbb{C}_{PAN}$ and Classifiers assigned by experts $\bar{\mathbb{C}}_{C_j}, \bar{\mathbb{C}}_{P_j}, \bar{\mathbb{C}}_{C_{r_j}} and\ \bar{\mathbb{C}}_{PAN}$ and model predicted classifiers $\bar{\bar{\mathbb{C}}}_{C_j}, \bar{\bar{\mathbb{C}}}_{P_j}, \bar{\bar{\mathbb{C}}}_{C_{r_j}} and\ \bar{\bar{\mathbb{C}}}_{PAN}$. In the supervised learning algorithm, all classifiers and variables must be independent (Marucci-Wellmana et al., 2017). For example, water pipe variables such as pipe diameter and pipe location are not statistically related. Therefore, NBC is an excellent candidate to be used in a water pipe system.

The following sections discuss model development and how the classifiers are assigned for both municipal engineers assigned classes and target classes. The mitigation algorithm ensures reproducibility on the defensible engineering decision, while the prioritization model provides explanatory evidence supporting the decision.

3.3 Model Development

The model is developed using NBC with supervised learning algorithm methods. The presence of target values in the training database makes the machine learning algorithm consider supervised learning (Iqbal & Yan, 2015). The variables V_{X_i} are selected using a pre-set bin threshold for properties measuring condition, performance, and criticality explained in Chapter 2. The model consists of several modules using the same MWN databases. The models' output classifies all water pipes within MWN based on their condition, performance, criticality. This model classifies capital work mitigation technology such as (Do Nothing, Rehabilitation, Replacement, and Upsize) for each pipe within the MWN.

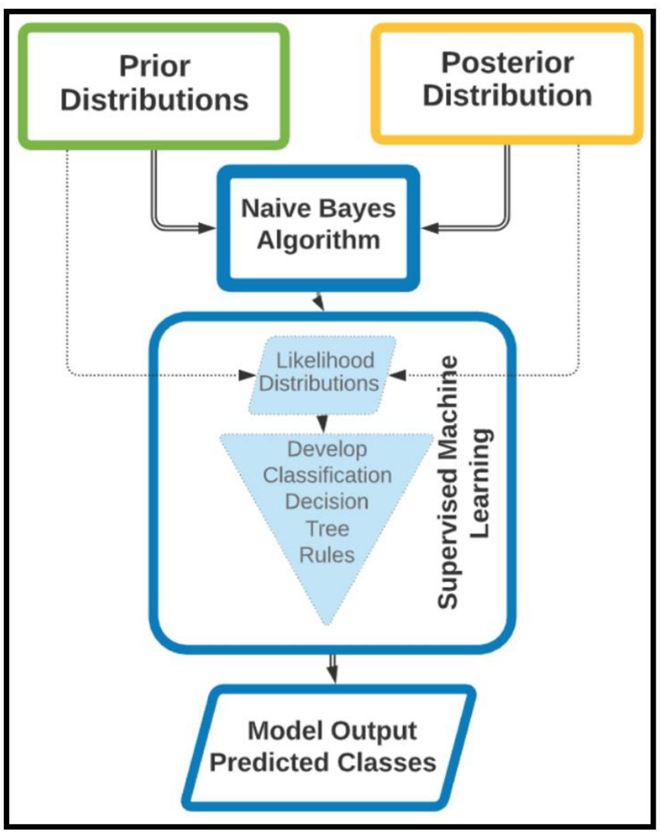

Figure 3-2 Supervised Naïve Bayes Learning Algorithm Flow Chart

Figure 3-2 summarizes the NBC model in a flow chart. The NBC model requires having prior, posterior, and likelihood distributions. As shown in Figure 3-2, prior and posterior classes are calculated from separate information for the same pipes within the same MWN. Variable values to calculate prior and posterior classes are gathered from two different sources. Prior classes are calculated using initial assigned variable values by a municipal engineer. Posterior classes or target classes are calculated using the survey results by asking professional engineers who are considered experts in the municipal water industry. Class boundaries are set based on the minimum and maximum scores calculated for all pipes within the database. The supervised machine learning algorithm calculates the likelihood distributions between each variable bin and posterior classes (target classes) to develop the decision tree matrix to replicate the information contained within the likelihood distribution.

Therefore, the NBC model is trained on posterior classes and is able to replicate the same classes for similar water pipes with similar attributes. Thus, the NBC, with a supervised learning algorithm model, is capable of repeating expert opinion for condition, performance, criticality, and mitigation classes.

3.3.1 Naïve Bayes Classifier

Bayes' Theorem is a simple but powerful prediction model widely used to perform classification tasks with a strong assumption of independence among variables (Nilsson, 1965). The NBC algorithm is a method that uses the probabilities of each variable belonging to each class to make a prediction (Kuhn & Johnson, 2013). It often performs well in many real-world applications, regardless of the strong assumption that features are independent in each class (Taheri & Mammadov, 2013). NBC assumes that all variables are independent of each other, and each variable only depends on the class (Taheri & Mammadov, 2012).

NBC is useful for high-dimensional data as the probability of each feature is estimated independently. If $\mathbb{C}_j$ represent the class (j) of an observation Variable Value V_{X_i}. Then, to predict the class of the observation $V_{X_{i+1}}$ by the Bayes rule, the highest posterior probability should be found. In the NBC, using the assumption that variables $X_1, X_2, X_3, \dots, X_n$ are conditionally independent of each other given the class.

$$P\left(\mathbb{C}_j|V_{X_i}\right) = \frac{P\left(\mathbb{C}_j\right)\ \prod_{i=1}^{n} P\left(V_{X_i}|\mathbb{C}_j\right)}{P(V_{X_i})} \qquad 3\text{-}5$$

NBC assumes the effects of a predictor V_{X_i} on class $\mathbb{C}_j$ that is assigned by the municipal engineer. All predictors or variables and their bins and all classes are independent. $P(\mathbb{C}_j)$ is the prior probability of each variable value in a particular prior class (j) that is initially assigned by a municipal engineer. $P\left(V_{X_i}|\mathbb{C}_j\right)$ is the likelihood probability of a pipe which the municipal engineer assigned variable V_X and bin (i) appear in class $\mathbb{C}_j$. $P\left(V_{X_i}\right)$ is the probability of a pipe within MWN that have engineer assigned variable value V_X and bin (i). $P\left(\mathbb{C}_j|V_{X_i}\right)$ is the posterior probability of class for a given predictor V_{X_i} that is variable (X) and bin (i). The goal of the NBC model is to predict a posterior class using the highest probability of occurrence of the predictor V_{X_i} on class $\mathbb{C}_j$ (Taheri & Mammadov, 2013) . This means the model determines the probability of a pipe with certain variable values V_{X_i} would be in certain condition class (j). The NBC model replicate the likelihood distribution $P\left(V_{X_i}|\mathbb{C}_j\right)$ using decision-tree-like-rules assuming that $P\left(\mathbb{C}_j\right)$ and $P(V_{X_i})$ are fixed, while being trained to the posterior distribution $P\left(\mathbb{C}_j|V_{X_i}\right)$. The NBC predicts a posterior probabilities using Equation 3-5 and expert assigned variable values. A supervised learning algorithm uses the prior and posterior distributions to the expected class $\bar{\bar{\mathbb{C}}}_j$ similar to expert assigned classes (target classes) $\bar{\mathbb{C}}_j$.

3.3.2 Supervised Machine Learning Algorithm

In the machine learning algorithm, each data point or water pipe in MWN is represented as a set of variables $(V_{X_1}, V_{X_2}, V_{X_3}\ \dots, V_{X_n})$. These variables could be continuous, categorical, or binary. When the training database have the same attributes and variable information as a known target class $\bar{\mathbb{C}}_j$, the learning scheme is recognized as supervised (Iqbal & Yan, 2015).

Supervised learning aims to build a concise model of the distribution of classes in terms of predictor features (Kotsiantis, 2007). Supervised learning is the machine learning task of learning a function that maps an input V_{X_i} to an output $\bar{\mathbb{C}}_j$ based on example, input-output pairs called target classes (Russell & Norvig, 2010). This process is called model training, and this target data is called training data consisting of a set of training examples (Mohri et al., 2012). The search algorithm looks for similar instances to train the NBC model using a training database with supervised machine learning to produce rules, making predictions in future instances using the same rules in other water networks, excluding the training database (Iqbal & Yan, 2015). In supervised learning, each example is a pair consisting of an input object (variable value) V_{X_i} and the desired output value (target class) $\bar{\mathbb{C}}_j$. A supervised learning algorithm analyzes the training data (target classes) $\bar{\mathbb{C}}_j$ and produces an inferred function (weights for each variable values), which can be used for mapping new examples (Russell & Norvig, 2010).

Machine learning rules are very similar to decision trees (Iqbal & Yan, 2015). The decision trees can be translated into a set of rules. A separate rule for all possible paths that predict a class (Salzberg, 1993). Therefore, the supervised learning algorithm is capable of replicating target classes $\bar{\mathbb{C}}_j$ that is assigned by expert with relatively high accuracy using the likelihood distributions $\prod_{i=1}^{n} P\left(V_{X_i}|\mathbb{C}_j\right)$ from Equation 3-5 (Furnkranz, 1999). Classification rules summarize likelihood distributions similar to decision-tree that applies the decision route to represent each class by the disjunctive normal distribution. If each data points have the same variable information V_{X_i} with known prior class $\mathbb{C}_j$ and target class $\bar{\mathbb{C}}_j$, then the learning scheme is known as supervised (Iqbal & Yan, 2015). The supervised learning algorithm goes through the database and adjusts the weights for each variable V_{X_i} after each line. Machine learning repeats the weight-adjusting over and over again to get the highest accuracy possible, predicting the target classes. By comparing the $\mathbb{C}_j$ and $\bar{\mathbb{C}}_j$ for all data points within the training database, the supervised learning algorithm is trained to predict the classes $\bar{\bar{C}}_j$ similar to target classes. Thus the model is trained to predict the target class with high accuracy.

The MWN database from a municipality in southern Ontario is used to develop and train this model. This model is tested on another MWN database from a different municipality in southern Ontario. Using NBC, supervised learning algorithms is a novel contribution to the water industry.

A comprehensive MWN database with all pipe attributes and variable values for properties measuring condition, performance, criticality, and mitigation is needed to have prior and posterior distributions and classes.

3.3.2.1 Prior Distribution

To compute the prior distribution $P(\mathbb{C}_j)$ for the prior classes $\mathbb{C}_j$ the model takes several steps using the municipality water network database. Figure 3-3 that is the left part of Figure 3-1 summarizes the prior distribution methodology. The following sections provide detailed information for all enumerated green sections included in Figure 3-3.

① As it is explained in Section 3.2 in this chapter, the MWN database contains all variables and variable values for every pipe within MWN to calculate Condition, Performance and Criticality Scores.

②Typically, municipal engineers at municipalities are responsible for identifying the factors and attributes to be used in prioritizing and planning Capital work, where these variables and attributes are measured and hence relevant to their municipality, based on their engineering judgment. Although the variable and variable bin thresholds are explained in Chapter 2, they can be changed as needed by different municipality unique MWN database. The municipal engineer assigned values is the initial assumption that will be benchmarked against the expert opinion.

③Municipal engineers assign variable values V_{X_i} are assigned based on their importance to all bins on the scale of 0 to 15 (0 to the least important and 15 to the most important) using their engineering judgment. The 0 to 15 scale is consistent for all variable values and scores.

④Condition, Performance and Criticality Score $S_C, S_P,\ and\ S_{C_r}$ and PAN for each pipe segment within MWN is calculated using Equations 3-1 to 3-4 with municipal engineer assigned variable values V_{X_i} and weights $W_C, W_P, and\ W_{C_r}$ for all pipes in MWN as it is shown in Table 3-3.

⑤All attributes(X), bins (i), variable values V_{X_i}, Condition Score S_C, Performance Score S_P and Criticality Score S_{C_r} and PAN that the municipal engineers assigned are determined.

Therefore, the NBC model can compute the frequency of each pipe occurrence in each class to compute prior distribution $P(\mathbb{C}_j)$ using Equation 3-5. The Maximum and Minimum Scores and PAN are calculated within the MWN. Figure 3-4 shows the sample frequency histogram for a few variables in the MWN. The NBC deduce all probabilities of different Scores and PANs.

Figure 3-5 shows sample probability density graphs for Scores and PAN for the MWN database. The O&P prioritization model requires having all variables distributed in the MWN.

⑥The NBC distributions classify the calculated municipal engineer Condition, and Performance Scores into five uniform classes (Very Poor, Poor, Moderate, Good, and Very Good) (P_{C_i}). The NBC classifies the Criticality Score into five uniform classes (Very High, Moderately High, Medium, Moderately Low, Very Low). As shown in Equation 3-6, the intersection of variable values represents a number that would identify the classes. The calculated number would fit into one classifier interval.

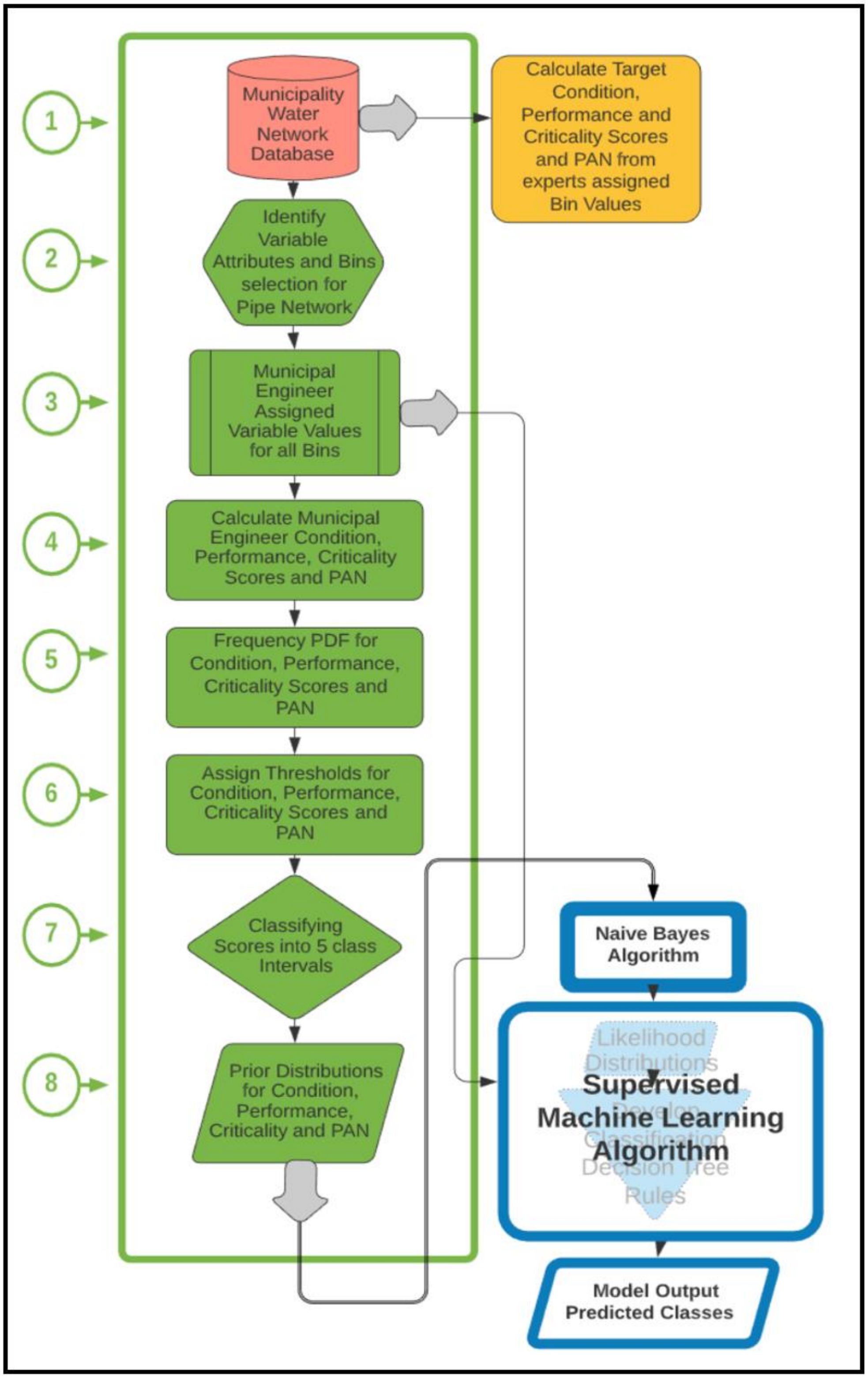

Figure 3-3 Posterior Distribution Flow Chart

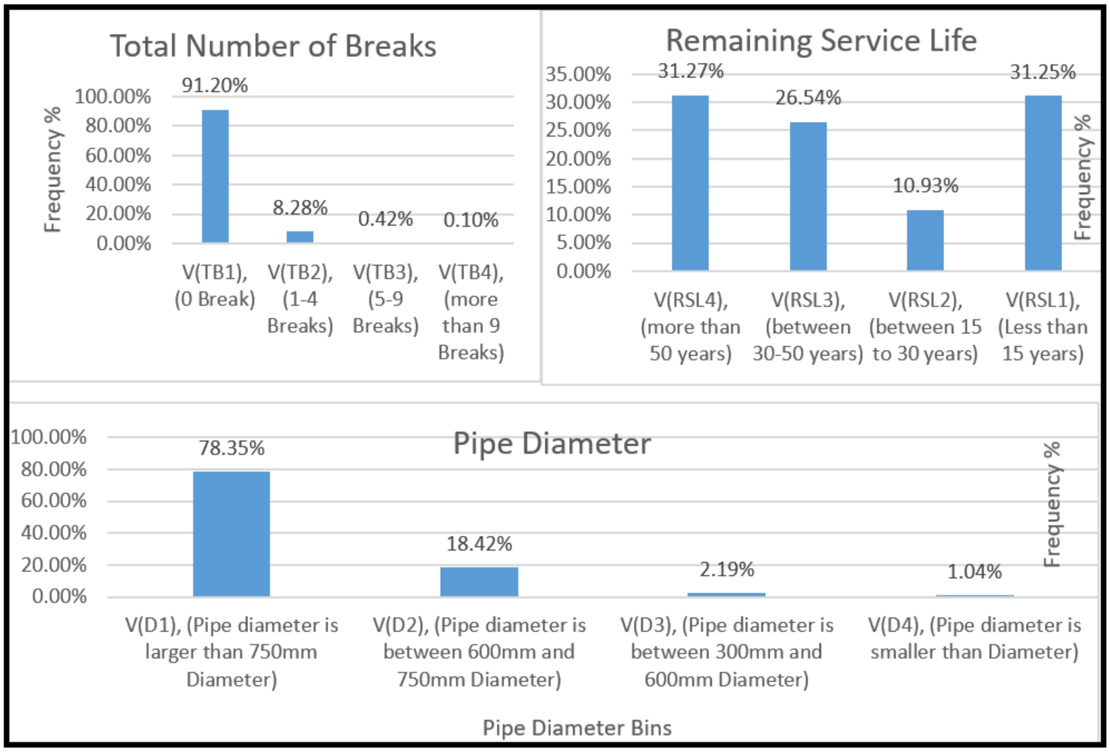

Figure 3-4 Frequency Histograms for a few Variables

$$(V_{X_i} \wedge V_{X_i} \wedge \ldots.) \equiv \mathbb{C}_{C_j} \tag{3-6}$$

All classifier's intervals are separated by equal size between the smallest and highest scores within the water network system. All intervals are evenly distributed between the best pipe and the worst pipe within the MWN. Equations 3-7, 3-8 and 3-9 show the calculation and

Table 3-4 shows the classifier's intervals.

$$\frac{(Larget\ S_C - Smallest\ \ S_C)}{5\ classes} = \ \ a_C \tag{3-7}$$

$$\frac{(Larget\ S_P - Smallest\ \ S_P)}{5\ classes} = a_P \tag{3-8}$$

$$\frac{(Larget\ \ S_{C_r} - \ Smalest\ \ S_{C_r})}{5\ classes} = a_{C_r} \tag{3-9}$$

Table 3-4 Municipal Engineer Class Intervals

Boundaries	Condition and Performance Class	Criticality Class
0 to smallest score + a_i	Very Good	Very Low
(smallest score + a_i) to (smallest Score + $2a_i$)	Good	Moderately Low
(smallest Score + 2 a_i) to (smallest Score + $3a_i$)	Moderate	Medium
(smallest Score + 3 a_i) to (smallest Score + $4a_i$)	Poor	Moderately High
(smallest Score + 4 a_i) to (smallest Score + $5a_i$)	Very Poor	Very High

The PAN is calculated using municipal engineer assigned variable values and weights with Equation 3-4 classified into four even intervals. The PAN intervals are the equal size between the smallest PAN and the highest PAN calculated for all pipes within the MWN. Equation 3-10 shows the calculation, and Table 3-5 shows the classifier's intervals.

$$\frac{(\text{Largest PAN} - \text{Smallest PAN})}{\text{Four classes}} = a_{PAN} \tag{3-10}$$

Knowing all classifier intervals, Scores, and PAN, the NBC classifies all pipes within MWN into five classes for Condition, Performance and Criticality and four Classes for PAN. Thus each water pipe within the MWN has a Condition Class, Performance Class, Criticality class, and Mitigation class.

Table 3-5 Municipal Engineer PAN Intervals

Boundaries	Target Class
0 to smallest PAN + a_{PAN}	Do Nothing
(smallest PAN + a_{PAN}) to (smallest PAN + $2a_{PAN}$)	Rehabilitate and Renovate Using Trenchless Technology
(smallest PAN + $2a_{PAN}$) to (smallest PAN + $3a_{PAN}$)	Replace with the Same Pipe Size
(smallest PAN + $3a_{PAN}$) to (smallest PAN + $4a_{PAN}$)	Replace with Larger Pipe Size – Up Size

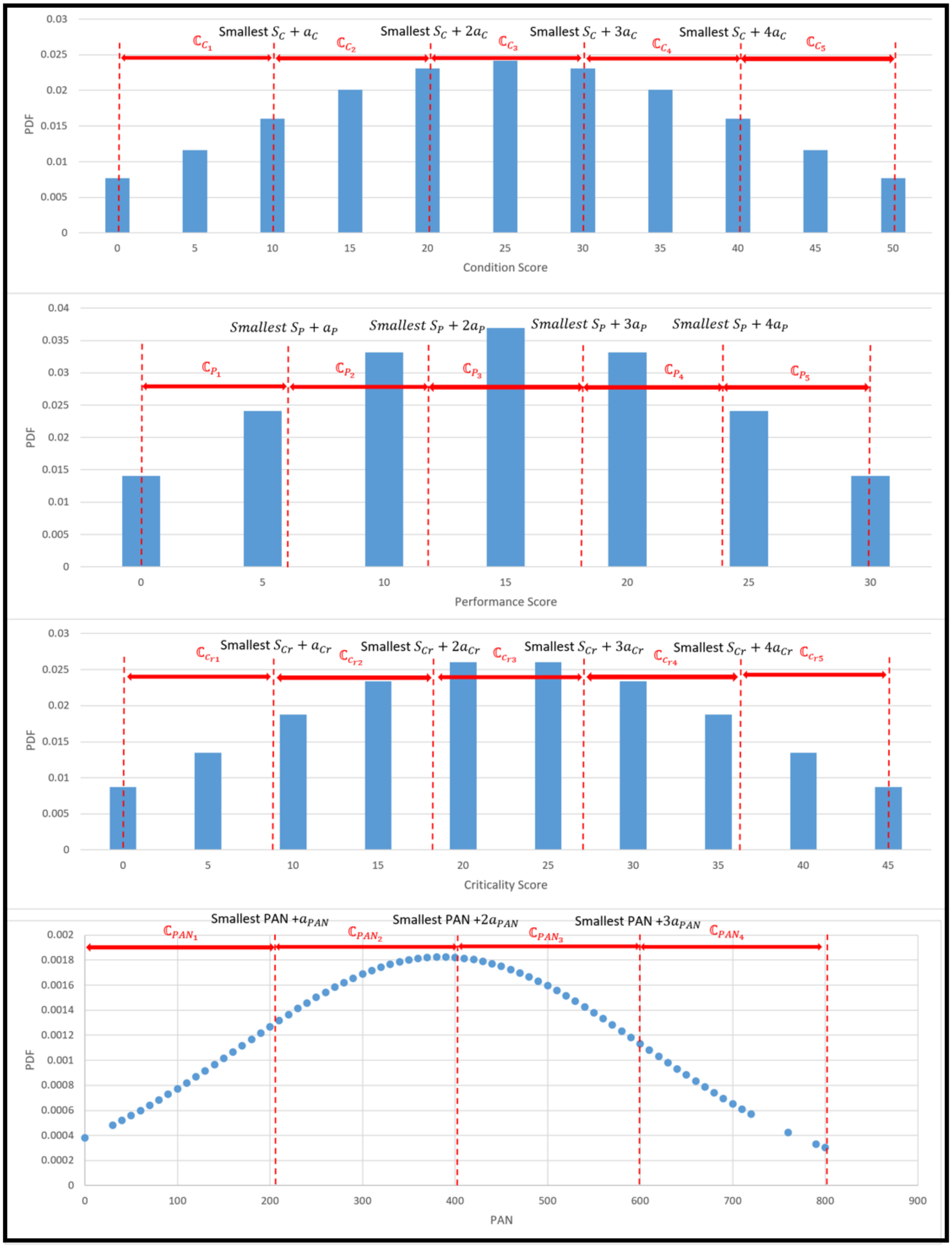

Figure 3-5 Probability Density of Different Scores and PAN

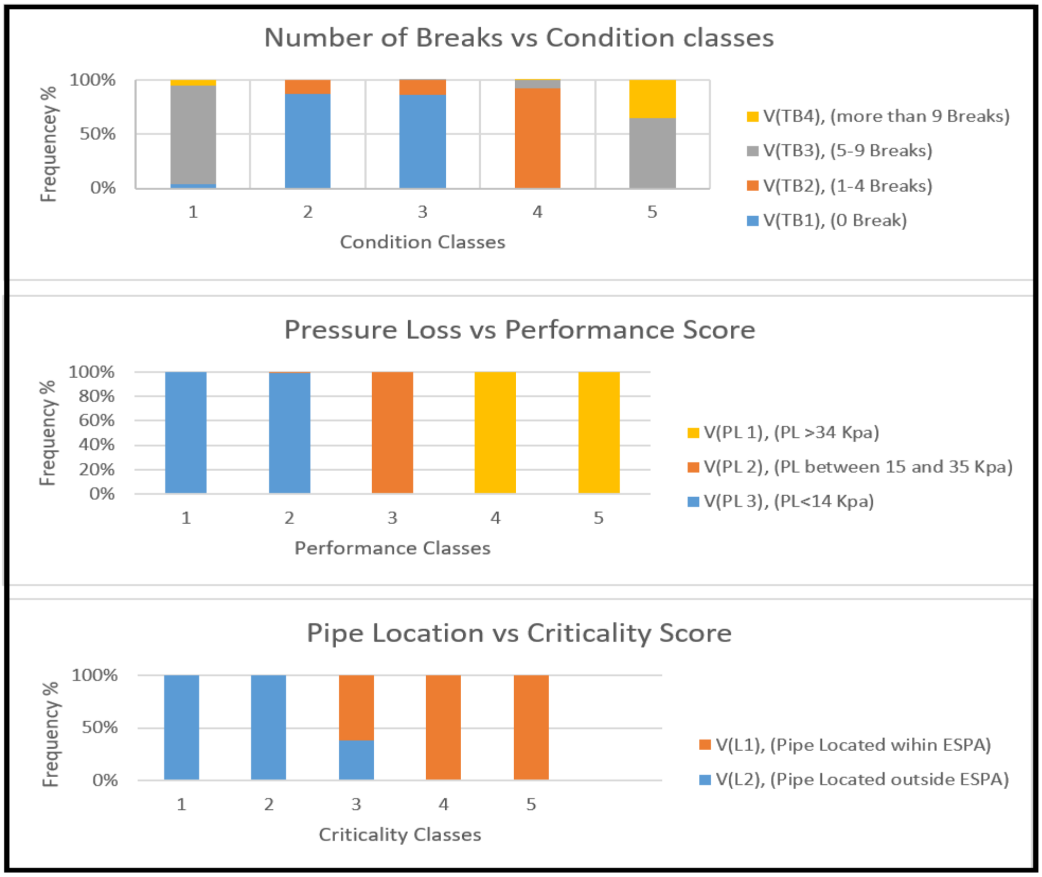

Figure 3-6 Sample Variable Value Frequency for Condition, Performance and Criticality Classes

⑧At this stage, when all municipal engineer assigned classes are known. The NBC will compute the frequency of a pipe within each bin that appears in each class for all Conditions, Performance, Criticality, and PAN, creating the likelihood distribution $P(X_i|C_j)$ in Equation 3-1. The model calculates all distributions for all possible pipe scenarios in the water network. These distributions are used as the prior distribution in NBC supervised learning.

Figure 3-6 shows a few frequency histograms as an example for Condition, Performance and Criticality Classes. NBC requires to have posterior distribution to continue.

3.3.2.2 Posterior Distribution

To compute the posterior distribution for the posterior classes model takes several steps. Figure 3-7 that is the right part of Figure 3-1 summarizes the posterior distribution methodology. The following yellow enumerated sections are referencing the numbers presented in Figure 3-7.

①The primary goal of the proposed methodology is to have a prioritized capital activities plan for MWN based on expert opinion. A survey questioner is prepared and circulated among experts in the municipal water industry to capture expert opinion. Survey preparation and model parameterization is explained in the next chapter in detail.

②In the survey questioner, the experts are asked to assign variable values $\bar{V}_{X_i}$ to all variables X each bin i that is identified by a municipal engineer explained in the previous section. All experts assigned variable values $\bar{V}_{X_i}$ and weights $\bar{W}_i$ are collected from the survey questioned, and they all are explained in the next chapter.

③The arithmetic means of all expert assigned variable values are used as the expert assigned a variable value $\bar{V}_{X_i}$ for each bin i. All survey questions, expert assigned variable bins, and arithmetic mean calculations are presented in detail in the next chapter.

④The Experts assigned variable values and weights are appointed all pipes in the MWN database. This is a link between prior $\prod_{i=1}^{n} P\left(V_{X_i}|\bar{C}_j\right)$ and posterior $P\left(\bar{C}_j|V_{X_i}\right)$ distributions (see Equation 3-5) that both distributions used the same database and the same network. Condition Score $\bar{S}_C$, Performance Score $\bar{S}_P$, Criticality Score $\bar{S}_{Cr}$, and $\overline{PAN}$ are once again calculated for pipe within the MWN using the expert's assigned variable bin values and weights. The scores calculated with the expert assigned values are called Target Scores and the $\overline{PAN}$ is called Target PAN. The same equations are used to calculate Target Scores and Target PAN as municipal engineer scores and PAN.

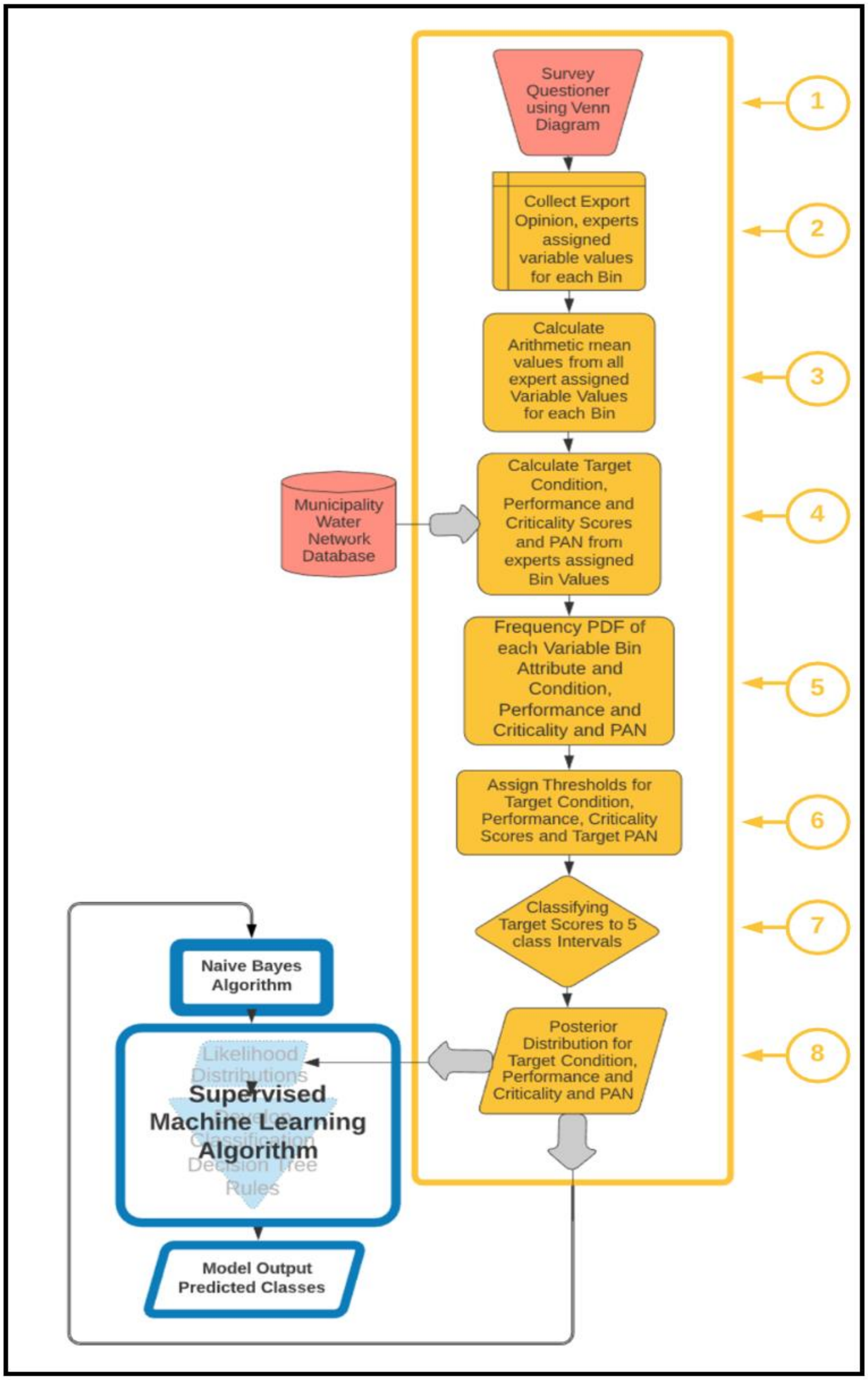

Figure 3-7 Posterior Distribution Flow Chart

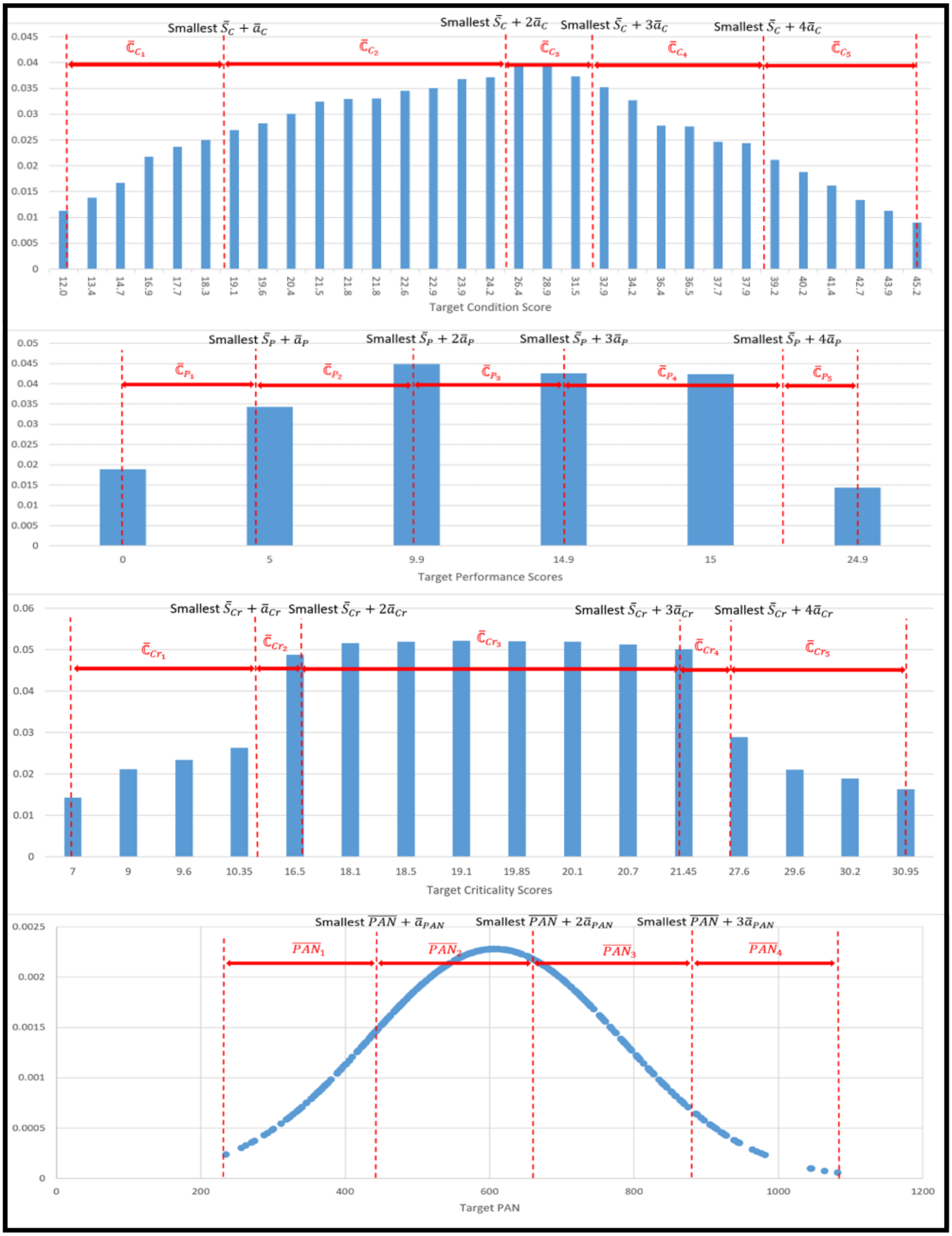

Figure 3-8 Probability Density of Different Target Scores and Target PAN

⑤Having all expert assigned variable values, Target Condition, Performance and Criticality Scores and Target PAN, the NBC model can compute the frequency of each pipe occurrence from the MWN in each bin. The Maximum and Minimum Target Scores and Target PAN are calculated for pipes in MWN. Figure 3-8 shows a sample distribution for Target Scores and PAN.

⑥Similar to municipal engineer assigned scores, Target Scores are classified into five uniform classes (Very Poor, Poor, Moderate, Good, and Very Good) for Condition, and Performance and (Very Low, Moderately Low, Medium, Moderately High, and Very High) for Criticality that is called Target Classes $\bar{\mathbb{C}}_j$. As shown in the equation, the intersection of all expert assigned variable values leads to a number that is fitted into a classifier interval for assigning a pipe class.

$$(\bar{V}_{X_i} \wedge \bar{V}_{X_i} \wedge \ldots.) \equiv \bar{\mathbb{C}}_{C_j} \qquad 3\text{-}11$$

All classifier's intervals are separated by equal size between the smallest Target Score and the largest Target Score calculated for pipes within the MWN system. All boundaries are evenly distributed between the best pipe and the worst pipe within the water network. Equations 3-12, 3-13 and 3-14 show the calculation and Table 3-6 shows the classifier's boundaries.

$$\frac{(Largets\ \bar{S}_C - Smallest\ \bar{S}_C)}{5\ classes} = \ \bar{a}_C \qquad 3\text{-}12$$

$$\frac{(Largest\ \bar{S}_P - Smallest\ \bar{S}_P)}{5\ classes} = \ \bar{a}_P \qquad 3\text{-}13$$

$$\frac{Largest\ \bar{S}_{Cr} - Smllest\ \bar{S}_{Cr})}{5\ classes} = \ \bar{a}_{Cr} \qquad 3\text{-}14$$

Table 3-6 Expert Assigned Class Intervals

Boundaries	Condition and Performance Class	Criticality Class
0 to smallest Target Score + $\bar{a}_i$	Very Good	Very Low
(smallest Target Score + c_i) to (smallest Target Score + $2\bar{a}_i$)	Good	Moderately Low
(smallest Target Score + $2\bar{a}_i$) to (smallest Target Score + $3c_i$)	Moderate	Medium
(smallest Target Score + $3\bar{a}_i$) to (smallest Target Score + $4c_i$)	Poor	Moderately High
(smallest Target Score + $4\bar{a}_i$) to (largest Target Score)	Very Poor	Very High

Target $\overline{PAN}$ computed using Equation 3-4. Target $\overline{PAN}$ classified into 4 uniform classes.

Target $\overline{PAN}$ classifier's intervals are assigned using expert opinion captured by survey results using several pipe scenarios. All water pipes within the MWN have a Target Mitigation class $\bar{\mathbb{C}}_j$ assigned to it.

⑦ Knowing all target classifier intervals, Scores and $\overline{PAN}$, the NBC classifies all pipes within the MWN into five classes for Target Condition, Performance and Criticality and 4 Classes for ($\overline{PAN}$) according to expert opinion. Thus, each pipe within the MWN has a Target Condition Class, Target Performance Class, Target Criticality Class and Target Mitigation Class assigned by expert opinion.

⑧All Target Classes are known, the NBC model will compute the frequency of a pipe within each bin that appears in each Target Class as the posterior distribution $P(\bar{C}_j/V_{X_i})$ in Equation 3-1 for all Conditions, Performance, Criticality and PAN. The model calculates all distributions for all possible pipe scenarios in the water network. These distributions are the posterior distribution in NBC supervised learning.

Figure 3-9 shows a few frequency histograms as an example for Target Condition, Performance and Criticality Classes.

At this stage, the NBC model has all $\mathbb{C}_j$ and Target $\overline{\mathbb{C}_j}$ classes. Based on the frequency of each occurrence, the learning algorithm will link between each bin variable (i) to the municipal engineer assigned class $\mathbb{C}_j$. Then compares the difference between the municipal engineer assigned class $\mathbb{C}_j$ and expert opinion Target Class $\overline{\mathbb{C}_j}$.

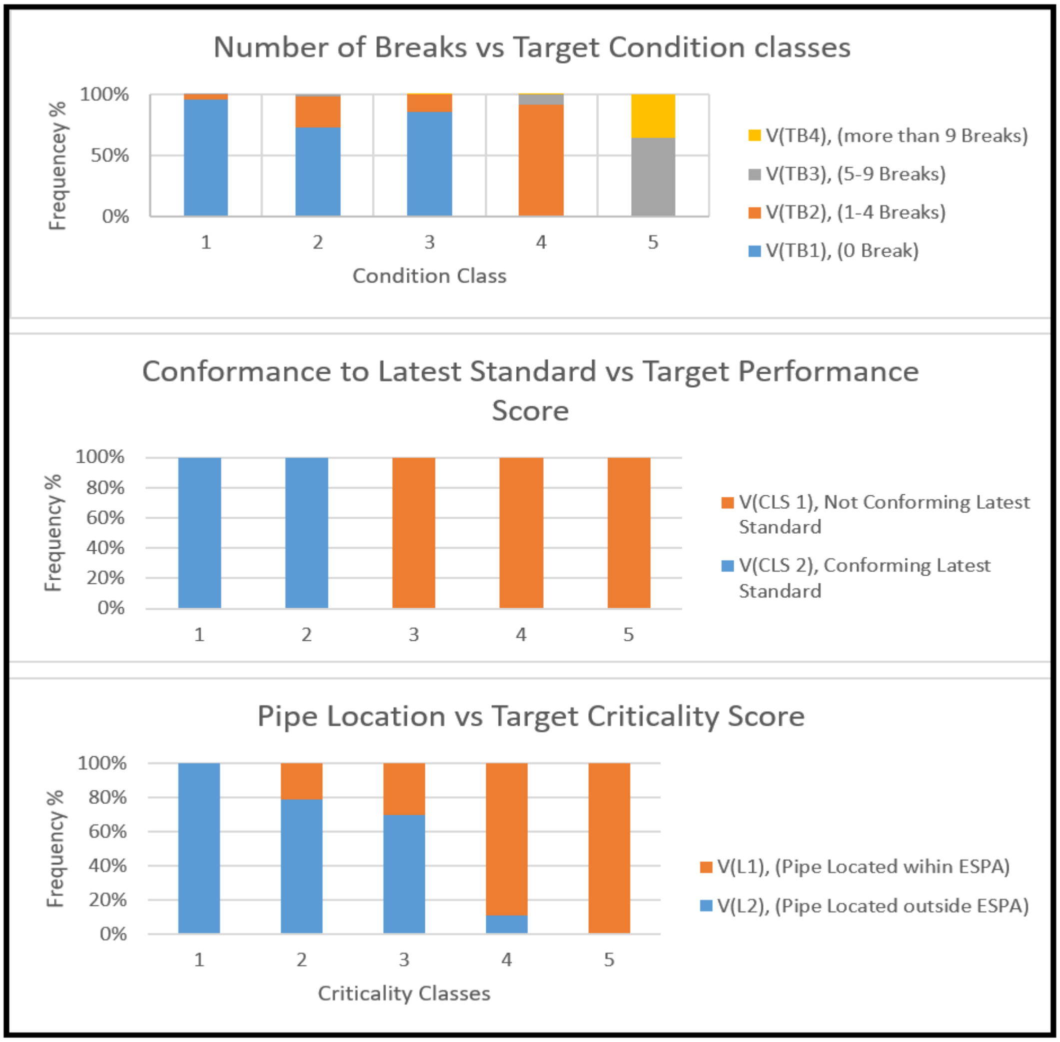

Figure 3-9 Sample Variable Value Frequency for Target Condition, Performance and Criticality Classes

3.3.3 Prioritization Models

The model outputs' first level is condition, performance, and criticality classes to prioritize all pipes in the MWN. For example, a pipe within the poor engineer assigned Condition Class

$\mathbb{C}_C = Poor$ and poor Target Condition Class $\bar{\mathbb{C}}_C = Poor$ would have variable V_{X_i} (X = total number of breaks (TB)) in$(i) = \ bin\ (more\ than\ 9\ breaks)$. The model predicts that pipe A belongs to the class $\bar{\bar{\mathbb{C}}}_C = Poor$, given the observations TB_1 (pipe A experienced more than nine breaks). The probability that pipes A is conditioned on V_{TB_1}; provided some evidence TB_1; what is the probability that pipe A belongs to a particular condition class $\mathbb{C}_1$. The NBC model computes all probabilities for all bins for all variables V_{X_i}.

$P(V_{X_i} \mid \bar{\mathbb{C}}_{Prioritation_j})$ estimated by $f\left(\bar{\mathbb{C}}_{Prioritization_j}(V_{X_n})\,\right)$. The classifier model sets the probability of expert predicted classes equal to model predicted classes. Therefore the model predicts the prioritization class $\mathbb{C}_{Prioritization_j}$ by assigning weights $\bar{\bar{W}}_{X_i}$ for each variable value. The probability of the model predicted class $\bar{\bar{\mathbb{C}}}_j$ based on the variable value V_{X_i} is:

$$P(\bar{\mathbb{C}}_j | V_{X_i}) \equiv P(\bar{\bar{\mathbb{C}}}_j | V_{X_i}) \quad 3\text{-}15$$

$$\bar{\bar{\mathbb{C}}}_j = \bar{\bar{W}}_{X_i} V_{X_i} + \bar{\bar{W}}_{X_i} (V_{X_i})^2 + \bar{\bar{W}}_{X_i} (V_{X_i})^3 \ldots \quad 3\text{-}16$$

$$\sum_{V_{X_i}}^{V_{X_n}} (\bar{\mathbb{C}}_j - \bar{\bar{\mathbb{C}}}_j)^2 \quad 3\text{-}17$$

The accuracy of the model is calculated based on comparing expert opinion assigned class $\bar{\mathbb{C}}_j$ and model forecasted class $\bar{\bar{\mathbb{C}}}_j$ for each pipe $\bar{\mathbb{C}}_j \equiv \bar{\bar{\mathbb{C}}}_j$. The NBC supervised learning algorithm adjusts the classifier prediction weights $\bar{\bar{W}}_{X_i}$ at every prediction (each pipe in the MWN) until the model prediction class is as accurate as possible comparing to Target Classes (expert's assigned classes) $\bar{\mathbb{C}}_j$. Therefore, after repeating the adjustment as many times as the number of data points (pipes in the MWN), the initial municipal engineer assigned class $\mathbb{C}_j$ is obsolete (Kotsiantis, 2007). The reason is model predicted classes are compared, and prediction weights are adjusted based on expert assigned classes $\bar{\mathbb{C}}_j$ as many times as the MWN pipes. The NBC supervised learning algorithm uses the deliberated weights from the training database and can apply them to any other MWN database with similar water pipe attribute information (Harvey et al., 2014). Therefore, using NBC supervised learning algorithm, assigning expert opinion on prioritizing water pipes for Condition, Performance, and Criticality is automated.

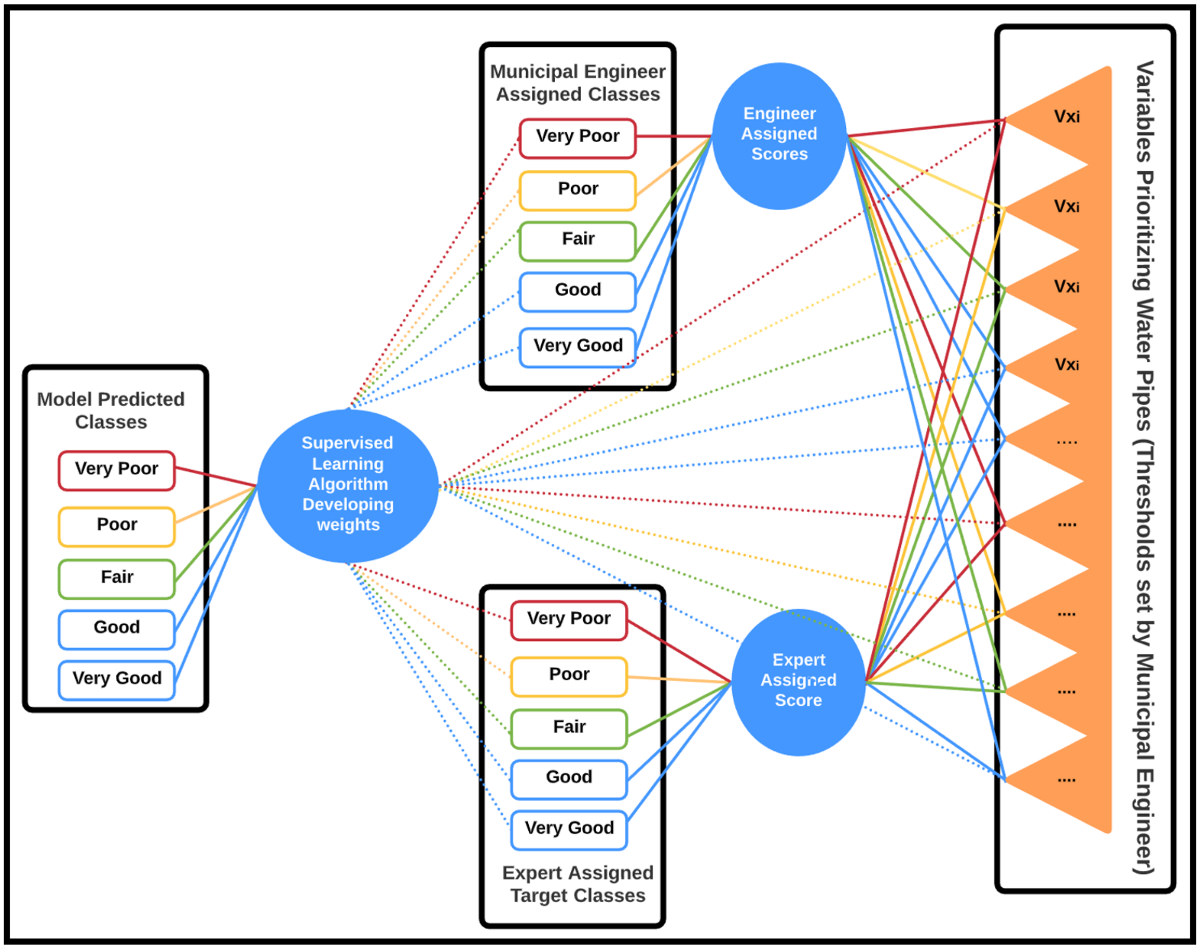

Figure 3-10 NB Prioritization Classifier Decision Tree

All problematic pipes with regards to condition, performance and criticality measurements are identified and marked using the prioritization models. The higher class pipes are to be considered for future investigation. The core function of supervised machine learning attempts is to ask an algorithm to automatically find a good predictor based on training data and repeat the decision after training for new instances (Iqbal & Yan, 2015).

Figure 3-10 visualized the learning algorithm that predicts classes using Municipal engineer assigned classes with the related variable for the corresponding prioritization model. Then compares the initial prediction with target classes assigned by experts to create weights $\overline{\overline{W}}_{X_i}$ for each variable. The learning algorithm repeats the comparison and weight adjustment process as many times as the number of pipes included in the MWN database. The model would then predict the same classes $\bar{\bar{\mathbb{C}}}_j$ for any other pipe with a similar attribute that is not in the training database. The proposed method will automate the condition prioritization for water pipes within a MWN database.

3.3.4 Mitigation Model

Having all pipe Condition, Performance and Criticality Classes, the mitigation model can make a capital work decision for each pipe through the MWN. The Mitigation Classifier predicts a mitigation class for each pipe in MWN by developing weights $\bar{\bar{W}}_{X_i}$ for each variable V_{X_i} similar to the Prioritization Classifier using Equations 3-15 to 3-17 with a training database. The supervised learning algorithm automates capital project decisions by predicting mitigation decisions like Target Mitigation classes $\bar{\mathbb{C}}_{PAN_j}$ for each pipe in MWN. The learning algorithm compares the predicted Mitigation Class $\bar{\bar{\mathbb{C}}}_{PAN_j}$ with the mitigation classes given by experts $\bar{\mathbb{C}}_{PAN_j}$ and adjust the predicted weights $\bar{\bar{W}}_{X_i}$ as many times as the number of pipes in the training database. The model continuously identifies pipe incidents, learns the probabilities and adapts weights $\bar{\bar{W}}_{X_i}$ for all variables until the model is capable of predicting the same Mitigation Class $\bar{\bar{\mathbb{C}}}_{PAN_j}$ as Target Class $\bar{\mathbb{C}}_{PAN_j}$ for pipes with similar variable values with high accuracy. The Learning algorithm repeats the comparison and weight adjustment until creating the weights that are capable of predicting the most accurate classifiers comparing with expert assigned classifiers $\bar{\mathbb{C}}_{PAN_j} \equiv \bar{\bar{\mathbb{C}}}_{PAN_j}$.

Figure 3-11 summarizes the decision tree logic of the Mitigation Model. The difference between the Prioritization models and Mitigation model are: (1) Prioritization models use different variable and variable values measuring condition, performance and criticality, but the mitigation model uses all variable values used in prioritization models. (2) The Target Mitigation Classes are assigned by experts directly using sample scenarios. In Prioritization models, the expert assigned classes are given using minimum and maximum scores.

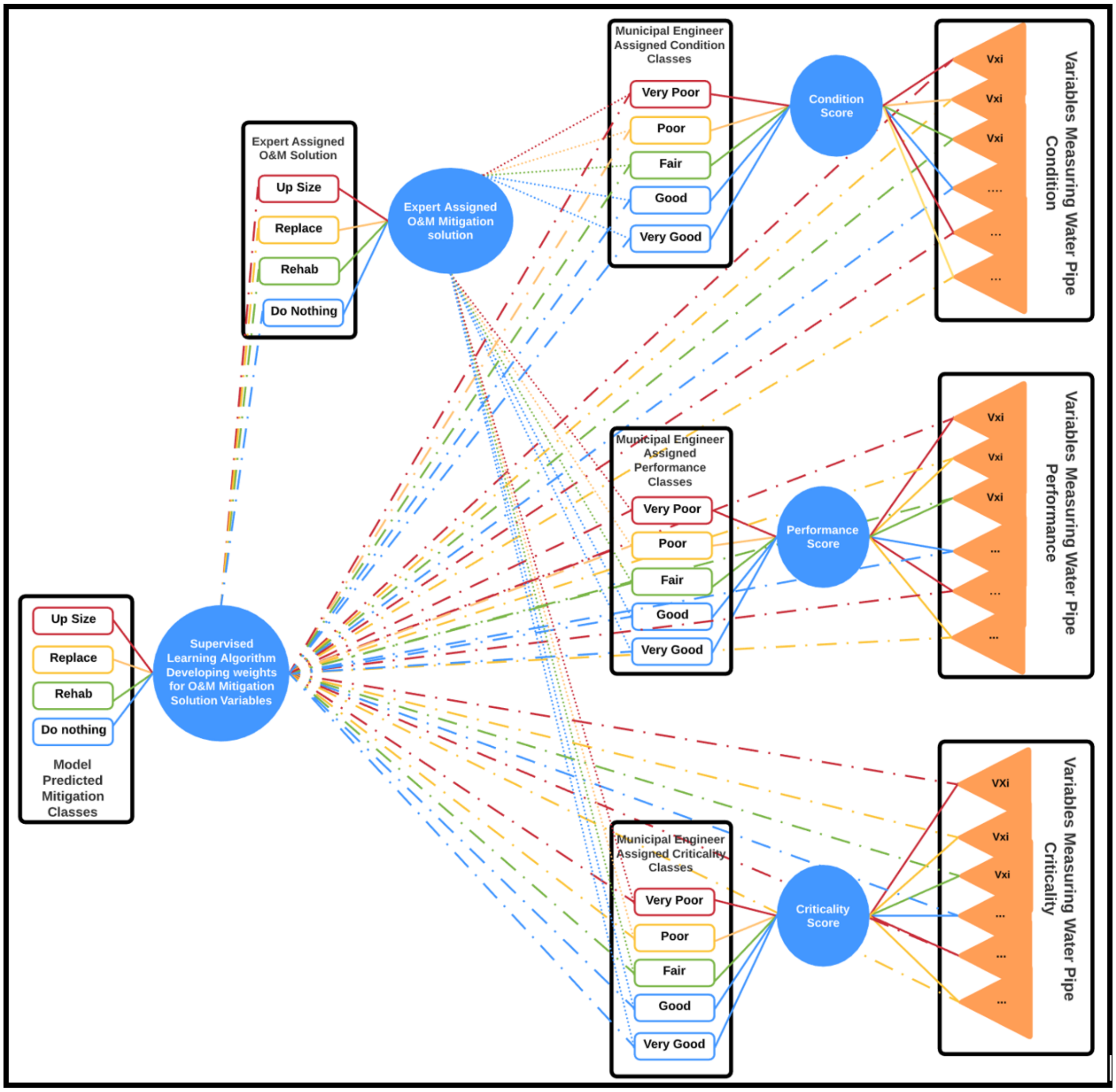

Figure 3-11 Mitigation Classifier Decision Tree

The supervised learning algorithm memorizes the developed rules from expert opinion and weights from the training database. The predicted weights $\overline{\overline{W}}_{X_i}$ are applied to deduce the same decisions for all future instances. Therefore, the Mitigation Model can replicate the expert opinion and engineering judgements on other MWN pipes that are not included in the training database. This model automates and standardizes the municipal engineer capital activities decisions according to the expert's judgement. This approach's utility is that NBC can be trained to replicate the capital project mitigation decision based on professional best practices.

The outcome of this approach is to introduce consistency and audit-ability into tactical and operational decisions making whereby engineering professionals select and stage sets of watermain pipes into projects for replacement and rehabilitation. All mitigation classes are populated in ArcGIS attribute data for each pipe. This automated engineering judgement algorithm would save municipalities resources (time, money and human resources). These much-needed resources could be used on much-needed capital and maintenance activities for ageing water infrastructure.

3.4 Conclusions

This chapter attempts to develop a novel approach that would be a valuable link between strategic, tactical, and operational levels to evaluate the Watermain system. This study could automate the capital planning process using an artificial intelligence machine learning algorithm that can replicate expert opinions. The first of its kind, the study investigates the feasibility of developing a multiple criteria scoring system and measures the weighting factors among different parameters to classify the condition, performance, and criticality of the Watermain section based on expert opinion. This attempt is using NBC supervised machine learning algorithms measuring the condition, performance and criticality of all water pipes within the MWN and assigned a capital work activity for all pipes in the MWN for the first time. Finally, this method could be applied as a decision-making support tool for a smarter, safer, faster, more consistent, defensible and reliable Watermain Capital activity decision-making system that saves taxpayers money.

This chapter is focused on model development and how to deduce the distributions and explained the supervised machine learning algorithm that classifies all pipes in the MWN. The next chapter will describe the expert opinion gathering with a scientific survey methodology and calculate the target values to parameterize the NBC model.

Chapter 4

Capturing Expert Opinion: Survey Questioner

Abstract

The municipal water planning needs to make prudent asset management decisions for water infrastructure projects. North American water infrastructure is beginning to show its age, particularly through water main breaks. Main breaks cause major disruptions in everyday life for residents and businesses especially in larger cities. North American municipalities are struggling to develop tools and processes that respond to the problem proactively instead of reactively (Kumar, et al., 2018). Barriers to a proactive maintenance program lack standard regulatory requirements due to complete condition, criticality and performance assessment of the entire system. In research provides complete condition, performance and criticality assessments using expert opinion gathered from a survey. The survey intends to gather expert opinion using a scientific methodology to set a standardized framework on prioritizing municipal water network capital activities. This methodology will add consistency and defensibility to capital programs.

Keywords: survey questioner, expert's opinion, engineer judgement, parametrization, ranking, mitigation technology, and capital work activity

4.1 Introduction

This Chapter is designed to capture expert opinions via survey questioner to prioritize condition, performance and criticality and provide a standardized engineering judgment on capital plan mitigation solutions for all pipes within the MWN. This effort is to develop a relatively standard repeatable and defensible engineering decision-making method for water assets within a municipal water network.

4.1.1 Background

Several studies have been completed to identify the essential water-pipes asset-management parameters in decision making (Poole, 2014). Aven (2016) suggests that decisions should be supplemented with expert opinion lacking historical data and standards. Engineering judgement and expert opinion vary by different people and different municipalities. The lack of standardized and structured planning for watermain pipe replacement or renewal affects the defence-ability of capital work decisions (Black & Veatch, 2018). Therefore, gathering expert opinions will provide a broader understanding of risk and uncertainty and make the decision-making process clearer (Linkov & Ramadan, 2005). Currently, the available methodology and the tangled nature of parameters affect the water system and the technologies applied to mitigate the matter are not standardized (West et al., 2017). Identifying important parameters affecting the watermain capital activities will also help improve frameworks and guidelines for the planning and watermain capital activities (Moglia et al., 2011). Despite considerable research on wastewater systems, few attempts have been made to explicitly define the complex water capital activities (Kunz et al., 2016).

Engineering judgment and expert opinion are aggregated by municipalities' geographical needs and specific water system requirements. The absence of standardized attributes for ranking water pipes for condition, performance and criticality results in a lack of reliable capital activity decisions by an expert (Jung, 2009). Table 4-1 summarizes the related research in ranking and prioritizing capital activities. Only three studies developed a survey to gather industry or expert opinion. The Ontario Sewer and Water Construction Association published a report in 2018 to rank the state of water and wastewater infrastructure in Ontario based on essential factors such as condition, performance and criticality. The general state of Ontario's watermains is ranked relatively poor for most municipalities. Although this report summarizes crucial factors in the ranking, it did not assign any resolution to improve the pipe state.

Table 4-1 Water Survey Literature

Related Research	***Includes a Survey that includes ranking criteria***	***Research Fields***	***Condition***	***Performance***	***Criticality***	***Mitigation***
Black & Veatch, 2018	Yes	Strategic Direction in the U.S.Water Industry	✓	✓	✓	✗
(OSWCA), 2018	Yes	State of Ontario Water and Wastewater Infrastructure	✓	✓	✓	✗
West et al., 2017	Yes	Expert opinion on risks to the long-term viability of residential recycled water schemes: An Australian study	✓	✗	✗	✗
Kunz et al., 2016	No	Drivers for and against municipal wastewater recycling	✓	✗	✗	✗
Carriço et al., 2012	Yes	Prioritizing Water Network Rehabilitation	✓	✓	✗	✓
Moglia et al., 2011	No	Multi-criteria decision assessments using Subjective Logic: Methodology and the case of urban water strategies	✓	✓	✗	✓
Jung, 2009	Yes	Sub Surface Linear Utilities	✗	✗	✓	✗
Linkov & Ramadan, 2005	No	Comparative Risk Assessment and Environmental Decision Making	✗	✗	✓	✓

Black & Vetch (2018) generated a report about the water industry's strategic decision that used condition, performance, and criticality variables to rank water pipes. There is no mitigation technology offered to improve condition, performance and criticality state of the pipe. West et al. (2017) gathered expert opinions to rank the recycling water usage in Australia, including water condition attributes for measuring long-term risks. They have created a survey to gather risk factors. Kunz et al. (2016) developed a list of essential criteria ranking municipal wastewater infrastructure. They only relied on condition variables in ranking models. Carrico et al. (2012) gathered information regarding prioritizing rehabilitation planned work for the water network. A survey is used to rank condition and performance variables in the prioritization model. Moglia et al. (2011) developed a multi-criteria decision assessment technique prioritizing capital activities on MWN. This research did not gather any expert opinion and only considered condition and performance criteria. Jung (2009) ranked the importance of the linear infrastructure based on their location and criticality variables. Some expert opinion is gathered for data comparison. Linkov & Ramadan (2005) compared risk assessments in prioritizing the maintenance activities, but only criticality factors are used in their research. No survey questioner is found in gathering expert opinion for ranking criteria and variables measuring condition, performance and criticality of water pipes. The knowledge gap is having a standardized method gathering expert's opinions for condition, performance and criticality of the water pipe. There is no standardized opinion mitigation solution to improve pipe conditions, performance and criticality scores.

4.1.2 Methodology

This chapter's main goal is to create, conduct and analyze results from an expert opinion survey in order to obtain target values of water pipe condition, performance and criticality ranking. The survey questioner also gathered expert's assigned mitigation decisions such as rehabilitation and replacement of water infrastructure. These target values are used to train a Naïve-Bayes-based supervised machine learning model. This study proposes an expert's opinion benchmark to the proposed decision support tool.

To address this knowledge gap, a survey questioner is prepared to gather expert opinions regarding the importance of criticality, condition, and performance on capital decisions. Experts are asked to assign capital activities to several pipe scenarios. The survey data has been used as target values to train the NBC model to replicate the expert opinion. Also gathers engineering judgment in mitigating a maintenance technology for different pipe conditions, performance and criticality. This study's results may provide a baseline that could potentially be used to benchmark the watermain performance measurement at different levels of municipal organizations. A method to capture expert opinion is proposed. This study would save municipalities much-needed resources by automating the screening process by categorizing data to classified score systems assigned by professionals. The learning algorithm is able to repeat engineering decisions automatically. This chapter will explain the database preparation effort, gathering expert opinion on a multi-objective mitigation scenario.

4.2 Survey Preparation

There are several survey questioner methods available (Sheatsley, 1983). The method used for this questioner is the special population method (Presser, et al., 2004). This method is designed in a way to facilitate easy answers for the participants to ensure clarity by rating using numbers to gather expert opinion. The method used in this questioner is called statistical modelling, developed in the 1950s and enhanced in 2004 by Biemer. This method allows researchers to design shorter scales that show more clear results (Couper & Miller, 2008). Using this method will shorten the questioner by eliminating the remaining area question and improving the survey's clarity by setting smaller boundaries (Reeve & Mâsse, 2004).

This survey is formulated using a common, consistent method to support the experts in consistently presenting their knowledge. All possible risk factors affecting water infrastructure are identified and asked to be ranked consistently. Hence, these factors are adopted as an expert opinion for setting target values explained in Chapters 2 and 3 for machine learning watermain planning mitigation. The mitigation technologies are clearly defined and presented in a four-by-four matrix. A five-point rating scale was adopted to enable ease of use Baxter et al. (2015) to reflect the scales commonly used in the industry. Participants are also requested to identify and rate any additional factors that could potentially impact water infrastructure.

To keep this survey in a manageable length, the Venn method has been employed. Venn method shows all possible logical relations between a finite collection of different sets in separate diagrams (Bardou et al., 2014). Also, using the Venn diagram method is aligned with the Naïve Bayes Algorithm requirement since it keeps all parameters separate and not related to each other for better consistency. Venn diagrams depict elements in the plane and sets as regions inside closed curves separate and not related to each other (Cipra, 2003). For this survey, it is assumed each curve represents one type of mitigation for pipe. For example, pipe replacement, up-sizing or rehabilitation. Therefore, sample scenarios are designed to capture the expert's opinions in overlapping areas to avoid repeating questions or add any confusion.

This survey set up in Survey Monkey and have three main sections. The first section collected information about the experts and their experience in managing water distribution assets. The second part is to rank the condition, performance and criticality of each water pipe by the expert to set target values $\bar{V}_{X_i}$ for prioritizing models. The survey result is used as target values $\bar{V}_{X_i}$ to train the model for the supervised learning algorithm to classify watermain pipe segments $\bar{\bar{\mathbb{C}}}_j$ to be able to replicate the expert's opinion or target classes $\bar{\mathbb{C}}_j$. Questions are set to gather expert's variable values $\bar{V}_{X_i}$ and assigned weights $\bar{W}_j$.

The five-point scale is deemed to reflect the scales commonly used in the industry. Hence expert's assigned values for each bin are adopted as an expert opinion for setting variable values $\bar{V}_{X_i}$. Participants are also requested to identify and rate any additional factors that could potentially impact water infrastructure. The survey results provided target variable values $\bar{V}_{X_i}$to calculate Target Condition Score $\bar{S}_{C_i}$, Target Performance Score $\bar{S}_{P_i}$ and Target Criticality Scores $\bar{S}_{Cr_i}$.

There are four ranking questions regarding pipe conditions. These questions are found in Appendix A1, Questions 12 to 15. The ranking questions are asked based on common current planning practices in Ontario. Hence, all survey participates should have been familiar with these questions, and their responses can reasonably be expected to be random samples of industry best practices. There are three ranking questions regarding the performance watermain. These questions are found in Appendix A1, Question 16, Part a, b and c. There are questions regarding the criticality measurement of the pipes. These questions are found in Appendix A1, questions 17 and 18. It is also asked if experts believe any other critical scenario they would like to add in this part. This part of the survey set the target values $\bar{V}_{X_i}$ for the first layer of the supervised NBC proposed automating initial water pipe assessment based on their condition and performance into five classes (Very Good, Good, Moderate, Poor, and Very Poor) and criticality into five classes (Very Low, Moderately Low, Medium, Moderately High and Very High).

The third part of the survey contained questions using different water pipe scenarios to capture engineering judgement on assigning capital decisions for each pipe fit to different scenarios.

Questions contain a specific pipe scenario using condition $\mathbb{C}_{C_j}$, performance $\mathbb{C}_{P_j}$, and criticality $\mathbb{C}_{Cr_j}$ classes to gather engineering decisions, mitigating pipe condition, performance and criticality. This is to set the target classes $\bar{\mathbb{C}}_{PAN_j}$ for the supervised NBC to mitigate a capital activity solution into four classes $\bar{\mathbb{C}}_{PAN_j}$ such as (Do Nothing, Rehabilitate and Renovate using Trenchless Technology, Replace the pipe with the same pipe Size and Replace the pipe with Larger Pipe Size (Up-Size)) for all pipes through the MWN. Table 4-2 summarizes all Target Classes used to classify all water pipes in MWN data.

Table 4-2 Target Classes

	Target Classes in Prioritization Model				
Classes / Attributes	1 (Very Good)	2 (Good)	3 (Moderate)	4 (Poor)	5 (Very Poor)
Target Condition Class	$\bar{\mathbb{C}}_{C_1}$	$\bar{\mathbb{C}}_{C_2}$	$\bar{\mathbb{C}}_{C_3}$	$\bar{\mathbb{C}}_{C_4}$	$\bar{\mathbb{C}}_{C_5}$
Target Performance Class	$\bar{\mathbb{C}}_{P_1}$	$\bar{\mathbb{C}}_{P_2}$	$\bar{\mathbb{C}}_{P_3}$	$\bar{\mathbb{C}}_{P_4}$	$\bar{\mathbb{C}}_{P_5}$
Classes / Attributes	1 (Very Low)	2 (Moderately Low)	3 (Medium)	4 (Moderately High)	5 (Very High)
Target Criticality Class	$\bar{\mathbb{C}}_{Cr_1}$	$\bar{\mathbb{C}}_{Cr_2}$	$\bar{\mathbb{C}}_{Cr_3}$	$\bar{\mathbb{C}}_{Cr_4}$	$\bar{\mathbb{C}}_{Cr_5}$

	Target Classes in Mitigation Model			
Classes / Attributes	1 (Do Nothing)	2 (Rehabilitation)	3 (Replace with the same Pipe size)	4 (Replace with larger pipe Size)
Target Mitigation Class	$\bar{\mathbb{C}}_{PAN_1}$	$\bar{\mathbb{C}}_{PAN_2}$	$\bar{\mathbb{C}}_{PAN_3}$	$\bar{\mathbb{C}}_{PAN_4}$

It assumed each Venn diagram curve represents one type of mitigation for pipe, for example, doing nothing, replacing with the same pipe size, and replacing the larger pipe size (up-sizing). Since each pipe only fits in one scenario due to its independent bins, the Venn diagram is a well-suited and useful methodology to keep scenarios separated and clear for an expert to understand. Figure 4-1 presents the Venn diagram used for different pipe scenarios.

Each question's pipe scenarios are designed to focus on the key variable that affects the expert opinion. For example, the difference between rehabilitation and replacement with the same pipe size is the pipe criticality. Due to the pipe's criticality, it would be beneficial to replace the pipe for the longer pipe life expectancy than rehabilitate it for shorter life expectancy. Questions are designed to cover all possible scenarios only once to keep the survey's length manageable.

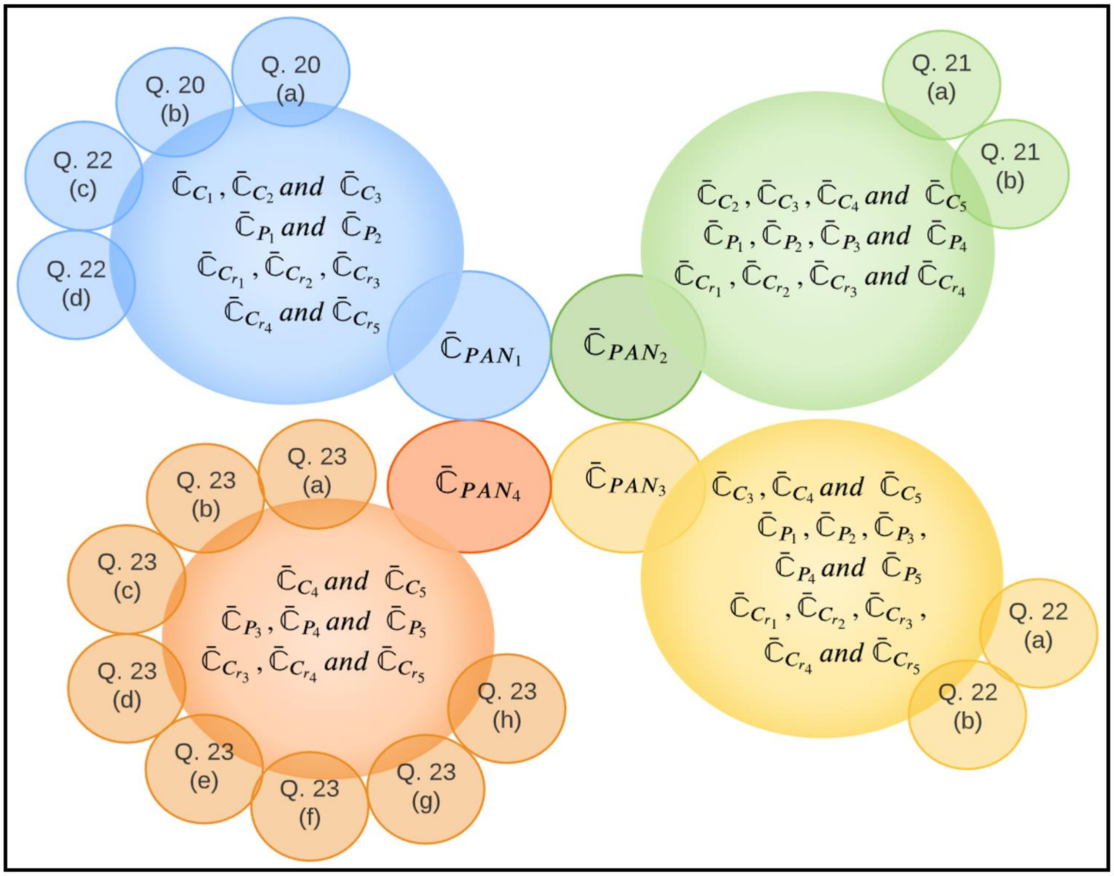

Figure 4-1 Venn Diagram for Different Pipe Scenarios

4.3 Parameterization of the NBC with Supervised Learning Model

The model includes two levels of analysis. This section explains the calculation of variable values for Mitigation Models and expert assigned mitigation technologies.

4.3.1 Survey Part I – Background Information about the Expert Respondents

The first part of the survey that included ten questions is designed to determine the level of expertise, type of decision that they make and the size of the municipality and projects that they have experience. Forty-four experts and decision-makers completed the survey. Figure 4-3 summarizes information about the experts who filled the survey. The majority of experts are from

Ontario, with only six from another Canadian province (two from British Colombia, two from Alberta, one from Nunavut, and Quebec). Figure 4-2 shows the spatial spread of expert's filled the survey questioner from the different municipality.

Table 4-3 Information about Experts who filled our Survey Questioner

Total number of experts that filled out the survey	44
Total number of experts from Ontario	38
Total number of experts from other provinces	6
Total number of experts that have an asset management group in their municipality	20
Total number of experts that have sufficient funds and a program for the next 5 five years	8
Total number of experts that have a large watermain network (more than 800 km) in their municipality	9
Total number of experts that have a watermain network with an average age between 50 and 70 years	15

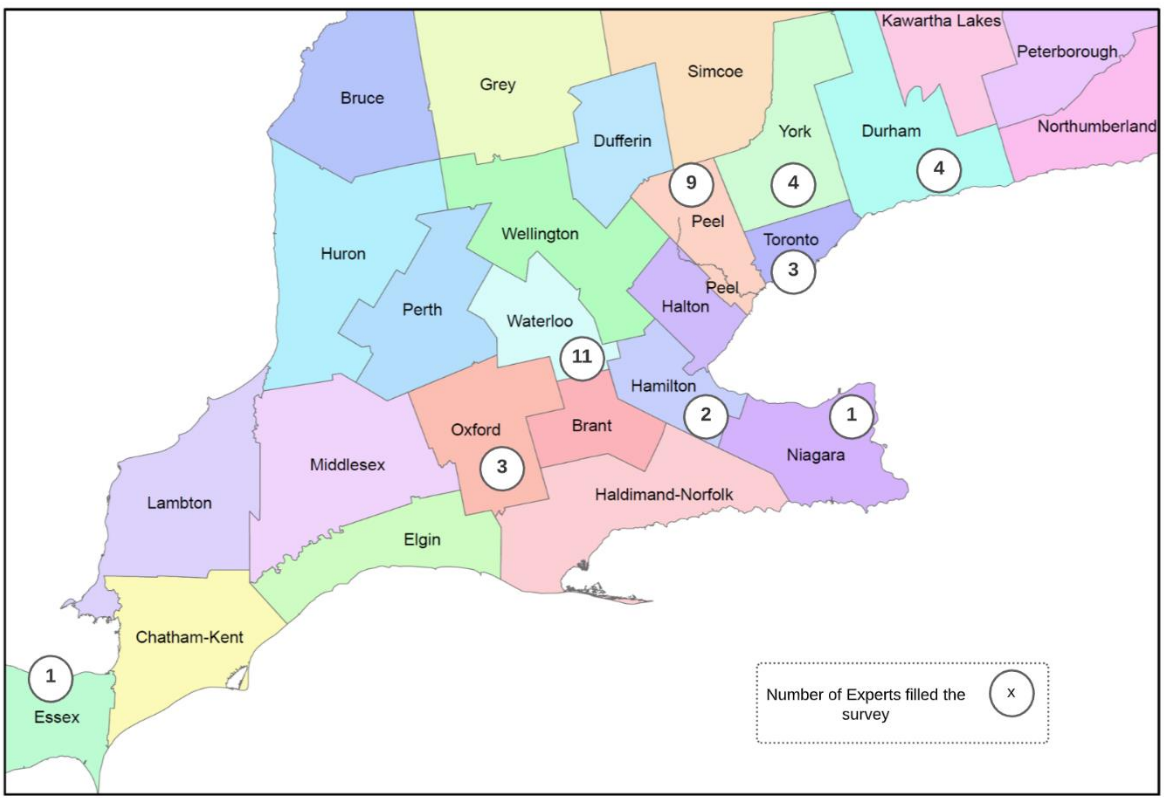

Figure 4-2 Number of Experts Filled the Survey Questioner from Municipalities in Ontario

Detailed information about survey results and all diagrams and data are presented in Appendix A2. Most experts are from large municipalities with more than 100,000 people population. According to this collected information about experts, they represent various experts who make decisions for water pipes. Therefore, no results are eliminated due to non-relevant experience.

Eighty percent of experts who filled this survey are capital decision-makers in their municipalities. Eighty percent have a separate asset management section and capital planning department for their water assets. Fifty percent y spent more than $10 million on their water system in the current fiscal year 2016. Thirty percent believed that their municipality has sufficient funds and budget for capital activities of their watermain system to keep the same service level. Forty percent believe that their municipality has sufficient programs and plans for the next ten years to maintain and keep the current level of service for their watermain system.

4.3.2 Survey Part II – Ranking Questions For Prioritization Models Target Variable Values

The questions are designed to match the variables and variable bins presented in Chapter 2 to calculate the expert assigned variable's values. Experts are asked to use their engineering judgement and experience to rank variables identified to measure the condition, performance and criticality of water pipes. The same scale is used in the entire survey, and the assigned score is used as a variable value for each bin. These expert's assigned variable values are used to calculate target score values of condition, performance and criticality and subsequently classify each pipe based on Table 3-3. The target classes are used to train the NBC with a supervised learning algorithm. Calculating target variable values $\bar{V}_{X_i}$ are explained in the following sections.

4.3.2.1 Target Condition Score ($\bar{S}_C$)

As in Chapter 2, four variables defined water pipe conditions: (1) The Remaining Service Life variable $\bar{V}_{RSL}$; (2) the total number of breaks variable $\bar{V}_{TB}$ (3) the total number of breaks in the last five years variable $\bar{V}_{TB5yrs}$; and (4) the maintenance index variable $\bar{V}_{MI}$. Each variable is dimensionless and enumerated using bins, where the values that bound each bin depend on assigned thresholds based on standard or criteria relevant to each variable. There are four questions regarding pipe condition: the importance of pipe age, pipe material, soil type, number of breaks that each pipe experiences (Question 12 to 15). These questions are presented in Appendix A1.

The variable values assigned by an expert via survey are used to calculate the Target Condition Score $\bar{S}_C$ using Equation 4-1.

$$\bar{S}_C = \bar{V}_{RSL_i} + \bar{V}_{TB_i} + \bar{V}_{TB5yrs_i} + \bar{V}_{MI_i} \tag{4-1}$$

4.3.2.1.1 Target Variable Values for Remaining Service Life ($\boldsymbol{\bar{V}_{RSL_i}}$)

To collect the expert's opinion regarding soil corrosiveness and its effects on water pipe remaining service life, experts answered questions 14 and 15. The expert's answers confirmed that experts believe soil corrosiveness will affect the pipe's service life. Therefore, the pipe material corrosion factor is needed.

To calculate the expert's pipe martial corrosive factor, two assigned life expectancies of the same pipe material in corrosive and non-corrosive pipes are deducted, then translated to a percentage to get the life reduction factor. For instance, experts believed the life expectancy of Asbestos Cement (AC) pipes in non-corrosive soil is 67 years and in corrosive soil is 49 years. As a result, experts believed corrosive soil would shorten the AC pipe's life expectancy by 18 years, equal to 26% of the total life expectancy. The same type of calculation is used to measure all corrosion material corrosion factors. Table 4-4 shows an expert's assigned expected service life for different pipe materials in corrosive and non-corrosive soils and calculated reduction factors.

Using expert corrosive factors, a single pipe's Remaining Service Life is calculated for every pipe in the system based on their soil type and soil environment. Below is a sample calculation for the Remaining Service Life in non-corrosive soil and corrosive soil for an AC pipe.

Table 4-4 Expert's Assigned Reduction Factors

Material Type $\mathcal{M}$	Expert's Opinion for Estimated Service Life of Different Pipe Materials in Non-Corrosive Soil Condition (Years)	Expert's Opinion for Estimated Service Life of Different Pipe Materials in Corrosive Soil Condition (Years)	Expert's Reduction Factor $\bar{\mathcal{R}}_{\mathcal{M}}$

Asbestos Cement (AC)	67	49	0.26
Cast Iron (CI)	84	63	0.25
Ductile Iron (DI)	71	52	0.26
PVC	85	81	0.04
CPP/CONC	88	66	1
HDPE	91	87	0.25

- The expected service life for an AC pipe is 70 years. The RSL for this pipe in corrosive soil would be calculated as:
- Using the assumed Reduction Factor (R_M) presented in Chapter 2: 50 – (0.1x50) = 45 years
- Expert's Reduction Factor ($\bar{R}_M$) calculated from survey results: 50 – (0.25x50) = 37.5 years

Experts asked to assign values to the different RSL bins for water pipes (Question 12). Table 4-5 summarizes all variable values assigned by experts to different RSL bins. The arithmetic mean or final target values $\bar{V}_{X_i}$ calculated and used in the model is presented in Table 4-5. All individual probability density histograms are in Appendix A2.

All variable values are introduced and explained in Chapter 2. The initial assigned variable values are called Municipal Engineer assigned values. The Municipal Engineer values are explained in Chapter 3, Figure 3-1, on the left side of the figure under the prior distribution section. All Municipal Engineer Assigned values are introduced in Chapter 3, Table 3-3 under Municipal Engineer Assigned Section. All Municipal Engineer-assigned variable values are on the scale of 0 to 15. The five-point rating scale (Baxter, Courage, & Caine, 2015) is used in the survey questioner. Therefore, to compare these two-scale, all five points variable values assigned by experts' via survey questioner are converted into an interval from 0 to 15 points to be consistent with the PAN in Chapter 2. The arithmetic mean values calculated to be used as expert's assigned variable values presented in 15 points in all the below charts.

Table 4-5 Expert Opinion Distribution for Water Pipes Remaining Service Life ($\bar{\boldsymbol{V}}_{\boldsymbol{RSL}}$)

How important is the Remaining Service Life of the Watermain for capital works (such as replacement or rehabilitation) decision-making? The score of 1 to 5 ("1" is not important while "5" is extremely important)							
				Survey Response			

Survey Question		$\bar{V}_{RSL_i}$	Bin Thresholds	1	2	3	4	5	Total Responses	Arithmetic Mean (0 - 15)
12 (a), 12 (b), and 12 (c)	Remaining Service Life of Pipe (Years)	$\bar{V}_{RSL_1}$	<15	0	2	8	15	2	28	10.5
		$\bar{V}_{RSL_2}$	15 - 29	5	13	8	2	0	28	6.7
		$\bar{V}_{RSL_3}$	30 - 50	20	2	2	2	2	28	5.1
		$\bar{V}_{RSL_4}$	>50	0	0	0	0	0	0	0

4.3.2.1.2 Variable Values for Total Number of Breaks ($\bar{\boldsymbol{V}}_{\boldsymbol{TB}}$)

To calculate the target values $\bar{V}_x$ for the water pipe number of breaks, experts asked to assign a value on the scale of 1 to 5 to each bin for the number of breaks that water pipe experienced in its lifetime (Question 13). Then the arithmetic mean of all numbers is assigned as the target variable value for each bin. All experts assigned value distributions are in Appendix A2. Table 4-6 shows all experts' assigned values and all arithmetic mean values calculated for each bin in (0 to 15 scale).

Table 4-6 Expert Assigned Value Distribution for Total Number of Breaks ($\bar{\boldsymbol{V}}_{\boldsymbol{TB}}$)

How important is the total number of Watermain breaks for Watermain capital works (replacement or rehabilitation) decision making? The score of 1 to 5 ("1" is not important, while "5" is extremely important).										
Survey Question	Total Number of Watermain Breaks	$\bar{V}_{TB_i}$	Bin Thresholds	Survey Response					Total Responses	Arithmetic Mean (0-15)
				1	2	3	4	5		
13(a), 13(b), 13(c) and 13(d)		$\bar{V}_{TB_1}$	≥9	0	2	0	9	18	29	13.4
		$\bar{V}_{TB_2}$	5 - 8	2	2	2	18	5	29	11.2
		$\bar{V}_{TB_3}$	1 - 4	8	5	14	0	2	29	7.2
		$\bar{V}_{TB_4}$	0	17	6	2	2	2	29	5.4

4.3.2.1.3 Variable Values for Number of Breaks in Last Five Years ($\bar{\boldsymbol{V}}_{\boldsymbol{TB5yrs}}$)

To eliminate confusion and repeat the total number of breaks question and keep the length of the survey manageable; no additional question asked regarding the number of breaks in the last five years. Therefore, the same assigned values as the total number of breaks to bins in the number of breaks in the last five years variable $\bar{V}_{TB5yrs}$.

4.3.2.1.4 Variable Values for Maintenance Index ($\bar{\boldsymbol{V}}_{\boldsymbol{MI}}$)

Since Maintenance Index is a calculated value and presented as a cost-benefit analysis method for the prioritization model, it is considered scientific and non-expert related. Therefore, there is no questions about this value. Thus, the same assigned values and bins are used for this variable. Table 4-7 summarized the assigned values for $\bar{V}_{MI}$.

Table 4-7 Assigned Variable Values for Maintenance Index ($\bar{\boldsymbol{V}}_{\boldsymbol{MI}}$)

MI Bins (i) ratio	Values ($\bar{\boldsymbol{V}}_{\boldsymbol{MI_i}}$)
>5%	15
1 – 5%	10
<1%	5

4.3.2.2 Target Performance Score ($\bar{\boldsymbol{S}}_{\mathbf{P}}$)

Three variables define Performance Scores S_P: (1) Water pipe Head-Loss pressure loss $\bar{V}_{HL}$; (2) Variable Water Quality $\bar{V}_{WQ}$ and; (3) Variable Conformance to Latest Standard $\bar{V}_{CLS}$. All variables and variable bins are explained in Chapter 2. The variable values assigned by experts via survey questioner are used as target values to set the Target classes for the performance model. Each variable is dimensionless and enumerated using bins, where the values that bound each bin depend on assigned thresholds based on standard or criteria relevant to each variable. The arithmetic means of all variable values assigned to each bin by experts are used to calculate the Target Performance Score $\bar{S}_P$ using Equation 4-2.

$$\bar{S}_P = \bar{V}_{HL_i} + \bar{V}_{WQ_i} + \bar{V}_{CLS_i} \qquad 4\text{-}2$$

There are four questions regarding the water quality and performance watermain, such as poor chlorine residual of the pipe, water quality complaints, and pipes no longer according to the current standard (Question 16).

4.3.2.2.1 Target Variable Values for Pressure Loss ($\bar{\boldsymbol{V}}_{\boldsymbol{PL}}$)

Since pressure loss is a scientific calculation using Bernoulli's equation, as it is explained in Chapter 2, there is no pressure loss question in the survey. Variable values are set on a scale of

0-15 based on the importance of a uniform scale. Table 4-8 summarized water pipe pressure-loss bins and their assigned variable values. The target variable values are the same as an engineer assigned variable values that are explained in Chater 2.

Table 4-8 Variable Values for Pressure-Loss ($\bar{V}_{PL}$) Bins

Pipe Diameter Categories		V_{PL}
HL for Small (0 – 600 mm) Bins i (Pressure-Loss)	HL for Large (≥ 600 mm) Bins i (Pressure-Loss)	
> 5.0	> 2.5	15
2.0 – 5.0	1.5 – 2.5	5
≤ 2.0	≤ 1.5	0

4.3.2.2.2 Target Variable Values for Water Quality ($\bar{V}_{WQ_i}$)

The three criteria considered for water quality variables are: (1) Water quality-related complaint, (2) Poor chlorine residual test, (3) Unlined CI (lead joint WM only). Questions asked experts regarding these criteria (Question 16). Table 4-9 shows all expert's answers, calculations, or the arithmetic mean value for each bin used as target values $\bar{V}_{X_i}$. Since this variable is binary, only one value is used as a target value. Therefore, the median of these three Arithmetic means is calculated for three criteria considered for this variable. Thus, water pipes that do not meet water quality criteria and are in these three categories are assigned the variable value $\bar{V}_{WQ_1}$= 10.7 for Water Quality.

Table 4-9 Expert Assigned Variable Value Distribution for Water Quality-Related Issues ($\bar{V}_{WQ}$)

Rank the following Watermain quality scenarios with respect to Watermain capital works (replacement or rehabilitation) decision making. The score of 1 to 5 ("1" is not important, while "5" is extremely important).									
Survey Question	$\bar{V}_{WQ_i}$	Parameters	Survey Response					Total Responses	Arithmetic Mean (0-15)
			1	2	3	4	5		
16(a), 16(b) and 16(c)		Watermain with poor chlorine residual tests	0	4	7	7	7	25	11

		Watermain with water quality-related complaints	0	3	10	5	7	25	10.9
		Unlined CI Watermain	0	5	8	8	4	25	10.3
	$\overline{V}_{WQ_1}$	Total Mean Value Used as Target Variable Value							10.7

4.3.2.2.3 Target Variable Values for Conforming Latest Standard ($\overline{\boldsymbol{V}}_{\boldsymbol{CLS_i}}$)

One question regarding this variable asks experts to assign their variable value to pipes that do not conform to the latest standard (Question 16). Table 4-10 showed all experts assigned values and the arithmetic mean value calculated based on the expert's assigned variable value. Therefore, value $\overline{V}_{CLS_1}$ =9.5 is assigned as the pipe's target variable value that does not conform to the latest standard.

Table 4-10 Target Value Distribution for Conformance of Latest Standard ($\overline{\boldsymbol{V}}_{\boldsymbol{CLS}}$)

Rank the following Watermain quality scenarios with respect to Watermain capital works (replacement or rehabilitation) decision making. The score of 1 to 5 ("1" is not important while "5" is extremely important).									
Survey Question	$\overline{V}_{CLS_i}$	Criteria	Survey Response					Total Response	Arithmetic Mean (0-15)
			1	2	3	4	5		
16(d)	$\overline{V}_{CLS_1}$	Watermain that was not installed according to current standards (for example, safe drinking water, engineering and construction design standard)	3	7	3	7	5	25	9.5

Variables chosen for performance may vary for each municipality since each municipality has a unique water system and requirement. The model's parameters are head loss that depends on the pipe material, pipe diameter and pipe length, water quality and compliance, and standard conformance. Water quality and standard pressure are very important to keep the service (Kunz et al. 2016). Some municipalities keep records of residents' complaints in different databases, and hard to access or cross-reference the data to the ArcGIS water network based on the limited provided information.

Also, standard change over time based on experience; for instance, led water services are not in standard due to toxic material, or some pipe diameter like less than 150mm diameter is not in standard based on reducing pressure. These standards vary in each city, and most often, these pipes are the priority and flagged for replacement and upsize. Therefore, water pipes that do not meet the latest standard are assigned the variable value $\overline{V}_{CLS_1}$ =9.5 for not conforming to the latest standard.

4.3.2.3 Target Criticality Score ($\bar{S}_{C_r}$)

As it is also explained in Chapter 2, three variables are defined to measure the criticality for water pipes: (1) Variable Pipe Diameter $\overline{V}_{D_i}$; (2) Variable Pipe Location $\overline{V}_{L_i}$ and; (3) Variable Pipe Accessibility $\overline{V}_{AC_i}$.

The Target Criticality Score $\bar{S}_{C_r}$ is equal to the sum of target variable values assigned to the above-mentioned variables using Equation 4-3.

$$\bar{S}_{C_r} = \overline{V}_{D_i} + \overline{V}_{L_i} + \overline{V}_{AC_i} \qquad \text{4-3}$$

This part includes two questions (17 and 18) that include a few sections covering criticality considered variables for water pipes. In these questions, experts are asked to rank the importance of pipe based on the consequence of failure in different water pipe scenarios such as pipes diameters, crossings highways, creeks, and environmentally sensitive areas, railway or hydro and gas crossings. It is also asked if experts believe any other critical scenario they would like to add in this part.

4.3.2.3.1 Target Variable Value for Pipe Diameter ($\overline{V}_{D_i}$)

To assign target values for the pipe diameter variable, the question is asked experts to assign a value to several pipe diameters (Question 17). All distribution histograms are in Appendix A2. Experts believed small pipes are important but not as important as large diameter pipes based on survey results. It means experts assigned ranked lower values to smaller pipe diameter and higher values to larger diameter pipes. Table 4-11 shows all distributions and calculated arithmetic mean values for all experts' opinions. The number of bins for pipe diameter is reduced, and a few pipe diameters are combined into one category. For example, water pipes <300 mm diameter are considered local according to the latest standard. Therefore, all <300 mm diameter pipes are fitted in one bin. Table 4-11 shows all experts' assigned values for each pipe diameter and the calculated arithmetic mean value used as the target value for experts' assigned values.

Table 4-11 Target Variable Values for Pipe Diameters ($\boldsymbol{\overline{V}_{D_i}}$)

Rank the importance of the following pipe sizes with respect to Watermain capital works (replacement or rehabilitation) decision making. The score of 1 to 5 ("1" is not important while "5" is extremely important)										
Survey Question		$\overline{V}_{D_i}$	Bin Thresholds	Survey Response					Total Response	Arithmetic Mean (0-15)
				1	2	3	4	5		
17	Pipe Diameters (mm)	$\overline{V}_{D_1}$	>900	2	0	4	8	8	22	11.7
			750 - 900	2	0	5	5	10	22	11.8
			Total Mean Value Used as Target Variable Value for >750 mm							11.8
		$\overline{V}_{D_2}$	600 - 750	2	0	4	14	2	22	10.9
			400 - 600	2	0	4	16	0	22	10.6
		$\overline{V}_{D_3}$	200 - 400	2	4	14	2	0	22	8.1
			Total Mean Value Used as Target Variable Value for 300 mm - 600 mm							9.8
		$\overline{V}_{D_4}$	200 - 400	2	4	14	2	0	22	8.1
			150	4	7	11	0	0	22	6.9
			<150	9	4	7	0	2	22	6.3
			Total Mean Value Used as Target Variable Value for <300 mm							7.1

4.3.2.3.2 Target Variable Value for Pipe Location ($\boldsymbol{\overline{V}_{L_i}}$)

This parameter is considered for a location that includes an Environmentally Significant Policy Area (ESPA). These variables are introduced and marked as a binary variable for water pipe Criticality Score S_{C_r}. Experts are asked to rank the importance of these variables on water pipes' capital activities (Question 18 parts a, b, c, d, and e). The rest of the previous expert's assigned values represent the importance of different pipe locations on Watermain capital activities. As it clearly is shown in Table 4-12, all experts recognized the importance of the ESPA.

Table 4-12 Expert Assigned Variable Value for Pipe Crossing the ESPA Location ($\boldsymbol{\overline{V}_{L_i}}$)

Rank the importance of the following pipe locations for Watermain capital works (replacement or rehabilitation) prioritization. The score of 1 to 5 ("1" is not important while "5" is extremely important)									
Survey Question	$\overline{V}_{L_i}$	Bin Thresholds	Survey Response					Total Response	Arithmetic Mean (0-15)
			1	2	3	4	5		
18(a), (b), (c), (d), and (e)		Watermain crossing watercourses such as creeks, rivers, and ponds	0	0	4	12	4	20	12
		Watermain servicing hospitals, airports, and long term care centres	0	2	2	8	8	20	12.3
		Watermain crossing power line corridors and high voltage poles	0	2	11	9	0	22	9.9
		Watermain crossing gas and oil pipelines	0	2	11	6	2	21	10.1
		Watermain crossing major intersections, highway crossings, and railway crossings	0	2	4	8	6	20	11.7
	$\overline{V}_{L_1}$	Total Mean Value Used for ESPA Target Variable Value							11.2

4.3.2.3.3 Target Variable Value for Accessibility ($\boldsymbol{\overline{V}_{AC}}$)

Similar to water pipe location, accessibility becomes an issue for Watermain capital activities. Areas, where accessibility to infrastructure may hamper corrective measures include: (1) Pipes with Narrow or No Access Easements, (2) Extra deep water infrastructure, (3) Pipes Located in Impassable Access by Vehicles. Questions are asked from experts to assign values based on the importance of accessibility via a survey (Question 18 parts f, g and h). Table 4-13 shows experts assigned values for water pipes with accessibility issues and the mean value calculated and used for water pipe accessibility in binary format.

Table 4-13 Expert Assigned Values for NOT Accessible Water Pipes ($\overline{\boldsymbol{V}}_{\boldsymbol{AC}}$)

Rank the importance of the following pipe locations for Watermain capital works (replacement or rehabilitation) prioritization. The score of 1 to 5 ("1" is not important while "5" is extremely important)									
Survey Question	$\overline{V}_{AC_i}$	Bin Thresholds	Survey Response					Total Response	Arithmetic Mean (0-15)
			1	2	3	4	5		
18(f), (g), and (h)		Watermain installed along narrow roads or with no easements	0	6	7	6	0	19	7.9
		Watermain installed extra deep (for example: deeper than 5m) below ground surface	0	4	4	12	0	20	10.2
		Watermain installed in areas without vehicle access	2	2	10	6	0	20	9
	$\overline{V}_{AC_1}$	Total Mean Value Used as the Target value for NOT Accessible Water Pipe							9

4.3.3 Survey Part III - Mitigation Model Target Classes

The final mitigation technology is assigned based on the highest number of assigned mitigation methodologies for each scenario. For example, 80 percent of experts agreed to be assigned the rehabilitate and renovate a pipe with many breaks located in an environmentally sensitive area. Another example, 89 percent agreed on open cut replacement of the pipe within bad condition but the low performance and criticality classes. The calculation target of variable values using the survey result is explained in the next section.

Table 4-14 summarizes all scenarios and links them to five different conditions, performance and criticality classes concerning survey questions. Using these results from an expert's judgement for different water pipe scenarios, the NBC supervised learning algorithm predicts a mitigating classifier similar to classifiers assigned by experts to water pipe scenarios presented in the survey questioner.

Table 4-14 Engineering Judgment Mitigating different pipe scenarios

For Pipe Group a) and b), select one of the following options: 1) do nothing, 2) renovate using trench-less technologies, 3)open cut and replace with the same pipe size, or 4) open cut and replace with largest pipe size:							
Survey Question	Class Combinations	Survey Response				Total Responses	$\bar{\mathbb{C}}_{PAN}$
		1	2	3	4		
20 (a),(b) 22 (c),(d)	Pipe condition in $\bar{\mathbb{C}}_C \in \{1,2,3\}$ Pipe performance in $\bar{\mathbb{C}}_P \in \{1,2\}$ Pipe criticality in $\bar{\mathbb{C}}_{C_r} \in \{1,2,3,4,5\}$	42	11	11	0	63	1
21 (a),(b)	Pipe condition in $\bar{\mathbb{C}}_C \in \{2,3,4,5\}$ Pipe performance in $\bar{\mathbb{C}}_P \in \{1,2,3,4\}$ Pipe criticality in $\bar{\mathbb{C}}_{C_r} \in \{1,2,3,4\}$	2	22	7	0	31	2
22 (a),(b)	Pipe condition in $\bar{\mathbb{C}}_C \in \{3,4,5\}$ Pipe performance in $\bar{\mathbb{C}}_P \in \{1,2,3,4,5\}$ Pipe criticality in $\bar{\mathbb{C}}_{C_r} \in \{1,2,3,4,5\}$	4	6	26	0	36	3
23 (a), (b), (c), (d), (e), (f), (g), (h)	Pipe condition in $\bar{\mathbb{C}}_C \in \{4,5\}$ Pipe performance in $\bar{\mathbb{C}}_P \in \{3,4,5\}$ Pipe criticality in $\bar{\mathbb{C}}_{C_r} \in \{3,4,5\}$	0	0	27	84	111	4

This model proposed the ability to repeat the engineering judgements on mitigating the condition, performance and criticality of every pipe through the entire MWN using a supervised learning algorithm. Inputs for this model are all variables used in prioritization models, and outputs are classified into four categories: Do Nothing, Rehab and Renovate using Trenchless Technologies, Replace, and Upsize. The same classes are used in the Naïve Bayes algorithm to keep classes and categories independent. Based on the survey questioner's captured engineering judgment data, a similar mitigation plan is assigned for each pipe through the entire water system using an expert's assigned classes by learning algorithm. The experts assigned values captured in the survey questioner are translated into a set of capital decision-making rules. Figure 4-3 visualizes the captured capital decision rules from survey results, as itemized in Table 4-14.

Figure 4-3 shows the two-level model; Level 1 (left part of the figure) shows prioritization model classifiers for Condition, Performance and Criticality. Level 2 (right part of the figure) summarizes the rules that are translated from the survey result. The translated rules from the survey are colour-coded, showing in this figure. The final Mitigation classifiers are listed in colour and linked to prioritization classifiers according to survey results. Each colour represents a mitigation classifier rule.

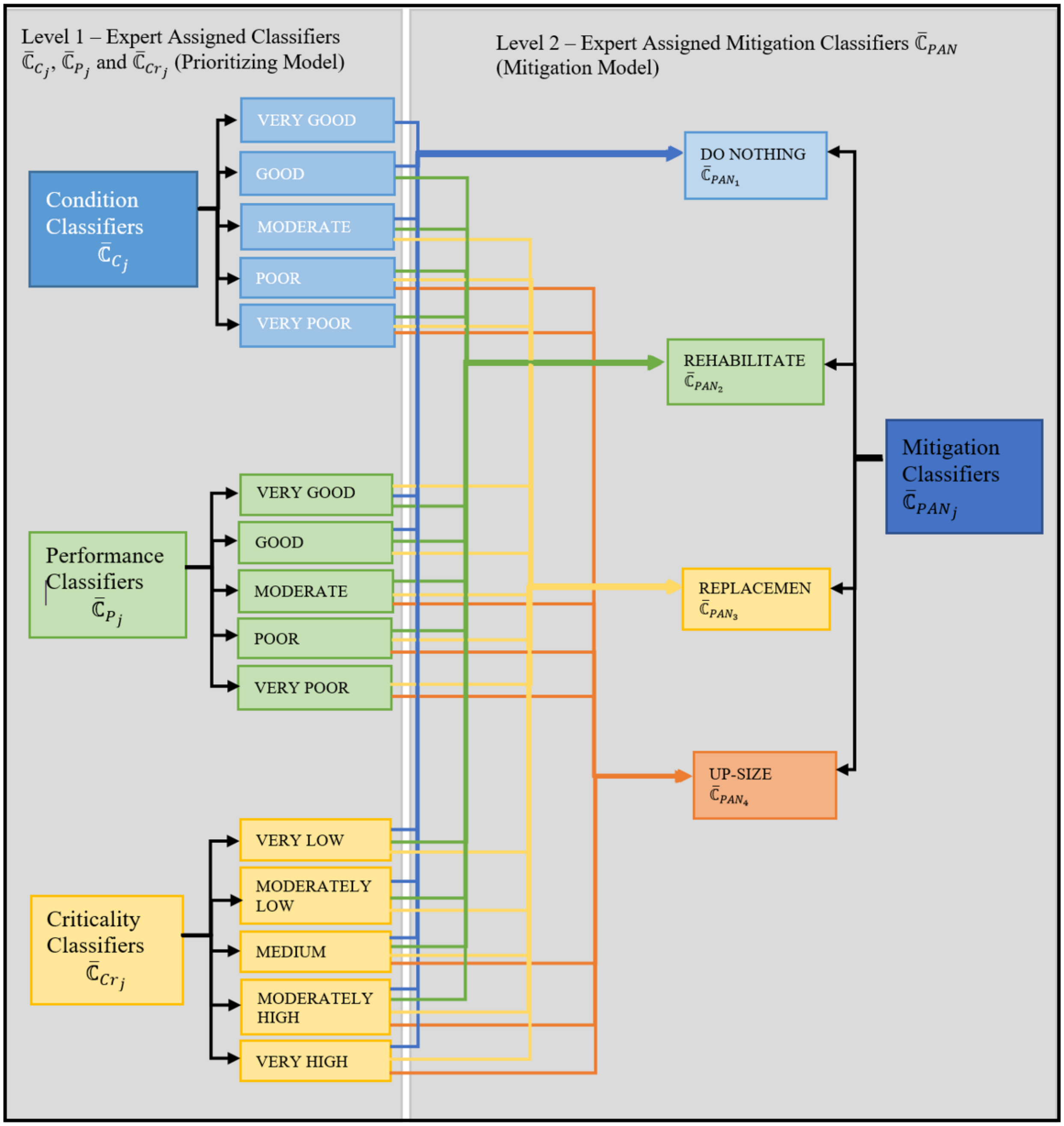

Figure 4-3 Experts Capital work Decisions

For example, the blue directional lines emanating from the condition, performance, criticality classifiers in the Level One model towards the Level Two model result in a “Do Nothing” mitigation classification. The blue lines contain condition classifier $\bar{\mathbb{C}}_{C} \in \{1,2,3\}$, performance classifier $\bar{\mathbb{C}}_{P} \in \{1,2\}$, and criticality classifier $\bar{\mathbb{C}}_{C_r} \in \{1,2,3,4,5\}$) in level 1 model and leads to "Do Nothing" mitigation classifier $\bar{\mathbb{C}}_{PAN_1} = 1$. This is the summary of the outcomes from questions 20 parts (a) and (b), 22 parts (c) and (d) in the survey. These rules are applied to similar pipe scenarios, and the classifiers are used as target mitigation classes. All classes are populated in ArcGIS attribute data for each pipe. The NBC supervised learning algorithm is capable of taking all input variables and replicates the engineering judgement with relatively high accuracy. The learning algorithm can replicate engineering judgment for all pipes through the water system in a very short time period.

The mitigation model's goal is to automate the capital decision-making process based on experts' standard and engineering judgements. The expert capital decisions observed from the survey translated to a set of decision rules to assign a mitigation technology to all pipes within the training database as Target Mitigation Class $\bar{\mathbb{C}}_{PAN_j}$.

4.4 Conclusions

Based on this research, the following conclusions can be drawn. This research is the first of its kind trying to standardize engineering decisions about water infrastructure. At present, however, there is no standard, defensible engineering decision-making technique for water infrastructure. The survey results confirm the chosen parameters are affecting factors water pipes condition, criticality and performance. Using this methodology, all pipes within the water system are ranked for their condition, performance and criticality. The proposed models are capable of replicating target scores, and maintenance activities are assigned from the survey's result capturing expert opinion and engineering judgement. The final model output identifies the most critical pipes to be replaced, rehabilitate and upsize based on expert opinion. This model would possibly provide bases for making more consistent, efficient, and reliable maintenance decisions.

This chapter focuses on gathering engineering judgement to rank individual pipe sections within water transmission and distribution lines and replicating the expert opinion using the supervised learning algorithm model's target variable values. Also, capturing expert opinion for capital activities for every pipe within the water system depends on its condition, performance and criticality. Survey results are set as target values for the supervised learning algorithms in the Naïve

Bayes model capable of replicating the entire watermain system's engineering decision relative to several parameters within a multi-criteria database.

This chapter is part of an attempt to develop a novel approach to automate engineering judgement and expert opinion regarding the condition, performance, and criticality of all pipes in MWN and mitigate the capital decision. To automate and replicate the expert opinion, there is a need to capture the expert’s opinion in a systematic methodology. The survey questionnaire apprehended engineering judgements and experts' opinions to build target values to parameterize the Naïve Bayes Classifier model's target values. Therefore, the model would be trained based on expert opinion and can replicate the engineering judgement.

The survey questioner is designed based on bins and thresholds set for PAN that are explained in detail in Chapter 2. The sensitivity analysis based on thresholds and survey results may be needed, but it is considered out of scope for this research. Also, a few expert's assigned variable values are considered as high for example, experts assigned value 5.4 to pipes that never experienced any breakage. This value is assumed 0 on Engineer assumed variable value.

These models are built on a very large database from a southern Ontario municipality and validated on another municipality database. The next chapter will explain the model results and show all the results in a case study. All results are explained in the next chapter. The method developed a valuable capital activity measurement tool to evaluate the current watermain system that is disaggregated from a certain type of pipe material, location, and any other limitation. This study's results may provide a baseline that could potentially be used to benchmark the watermain performance measurement at different levels of municipal organizations. A scientific prioritization model that is based on expert opinion is proposed. This research attempts to develop a novel approach that would be a valuable link between strategic, tactical, and operational levels to evaluate the watermain system.

Chapter 5

Model Application: Case Study

Abstract

The proposed multi-level NBC with a supervised learning algorithm can replicate engineering judgement. This model is applied to the prepared comprehensive database from London, Ontario. This chapter presents a descriptive analysis of the water network pipes for their condition, performance and criticality, and capital activities decisions regarding all pipes within the London database. Different maintenance and capital work scenarios are presented and compared with the actual 2016 and 2017 replacement programs from the City of London to validate the accuracy of the proposed model.

This methodology will add consistency and defensibility to capital programs. Using this algorithm can help utility save money by automating industry best practices and optimizing long-term decisions about the order in which pipes need to be staged into your capital works programs.

Keywords: model application, case study, municipal water network, prioritization model, mitigation model, do nothing, replacement, rehabilitation, up-sizing, capital work activities, validation, and verification

5.1 Introduction

Assigning capital work activity for a water pipe called mitigation decision in this research requires information such as pipe condition, performance and criticality. Past studies have focused on pipe condition and physical attributes as a primary decision-making factor for capital activities. There are several prioritizing methodologies in the water industry, but only a few models are applied and tested on real water pipe data. Using complicated models on imperfect water pipe data often shows ineffective results (Savic, 2009).

The literature for models applied on real data for water pipe began to appear in the 1980s (Rogers & Grigg, 2009). Several modelling methodologies are tried in different MWN databases so far. (1) Economic models define the present worth of a pipe's operation and maintenance costs based on its remaining service life and replacement costs, using different statistical models to forecast the number of breaks. This model is applied to St. Louis, Missouri MWN database to prioritize the water pipes as part of a replacement program (Grablutz & Hanneken, 2000). (2) Mechanistic models are focused on pipe physical deterioration attributes, such as; temperature, pressure, frost stress, corrosion due to soil properties, pipe coatings, water quality parameters, and installation depth (Agbenowosi, 2000). These models were used in Des Moines, Iowa, to prioritize watermains for different soil conditions by McMullen (1982) and Winnipeg, Manitoba, to prioritize watermains by pipe diameter (Kettler & Goulter, 1985). (3) Probability models attempt to predict the probability of pipe failure in future time during the pipe life cycle. Several versions of this model are applied on the MWN of New Haven, Connecticut, by Marks (1985) and Andreou (1986). This model is also applied to MWN data in Paris, France, by Brémond (1997). A probability model called KANEW, created by Deb et al. (1998) is applied to Denver, Colorado MWN data. AWWA funded a study in 2001 to forecast future pipe replacement for 20 different municipalities throughout the United States using the KANEW model. This model is currently used in the City of Toronto to benchmark the water capital activities. (4) Deterioration Point Assignment methods define a set of failure contributor factors such as pipe age, pipe material, location, soil type, and break history. This method uses the different categories and assigned weights for each factor. A total score is calculated for each pipe. If the total score exceeds the threshold value, then the pipe is a candidate for renewal (Loganathan et al., 2002). This model was used to evaluate Louisville Water, Kentucky.

Table 5-1 summarizes all past models applied to the MWN database. It demonstrates no comprehensive method that prioritizes capital work technologies such as rehabilitation and replacement of water infrastructure while measuring condition, performance, and criticality attributes of each pipe based on expert opinion have been applied or validated using a MWN database. Also, machine learning methodologies have not been used in water pipe capital activities to prioritize pipe segments for mitigation technologies. Thus far, no comprehensive model available to consider all pipe factors measuring condition, performance, and criticality and proposes a capital works mitigation technology for each pipe through the water system.

Table 5-1 Water Pipe Modeling Criteria

	Ranking Criteria			
Real Data Modeling Literature	***Condition***	***Performance***	***Criticality***	***Mitigation***
Economic models or Cost-Benefit Models				
Grablutz & Hanneken, 2000	✓	×	×	×
Mechanistic models				
McMullen, 1982	✓	×	×	×
Kettler & Goulter, 1985	✓	×	×	×
Agbenowosi, 2000	✓	×	×	×
Regression and Failure Probability Methods				
Marks, 1985	✓	×	×	×
Andreou, 1986	✓	×	×	×
Brémond, 1997	✓	×	×	×
Deb et al., 1998	✓	×	×	×
Deterioration Point Assignment (DPA) Methods or Scoring System method				
Loganathan et al., 2002	✓	✓	×	×

This chapter aims to collect and organize observations and measurements relating to the City of London's watermain network into attributes pertaining to condition, performance, and criticality scores. Thereafter, this information is used to construct a MWN database connected to the machine-learning model. The model is used to rank every watermain segment within the network for condition, performance, criticality, and suggested mitigation technologies. Model verification is assessed by replicating the prioritization of pipe segments and mitigation technologies chosen by City of London municipal engineers as part of their 2016 and 2017 watermain capital works programs.

In this chapter, the PAN classification $\mathbb{C}_{PAN_j}$ using municipal engineer-assigned variable values and the calculation of all initial municipal engineer-assigned classifiers $\mathbb{C}_{C_j}$, $\mathbb{C}_{P_j}$ and $\mathbb{C}_{Cr_j}$ are compared with the expert's assigned classifiers $\bar{\mathbb{C}}_{PAN_j}$, $\bar{\mathbb{C}}_{C_j}$, $\bar{\mathbb{C}}_{P_j}$ and $\bar{\mathbb{C}}_{Cr_j}$. All symbols are explained in Table 3-3 in Chapter 3.

All variables and engineer-assigned variable values are organized in a comprehensive shapefile explained in section two. The sum of the engineer-assigned variable values V_{X_i} is Condition Score S_C, Performance Score S_P and Criticality Scores S_{Cr}. The engineer-assigned classifiers are categorizing all scores into five uniform classes between the minimum and maximum calculated scores. The engineer-assigned PAN is the sum of all scores multiple by an engineer-assigned corresponding weight W_C, W_P and W_{Cr}. Engineer-assigned mitigation classifier $\mathbb{C}_{PAN_j}$ is also assigned based on the minimum and maximum PAN.

All expert's assigned variable values $\bar{V}_{X_i}$ or target variable values calculated using the arithmetic mean captured from the survey. All target variable values are organized in a MWN database GIS attribute table. The sum of expert's assigned variable values are expert's assigned scores $\bar{S}_C$, $\bar{S}_P$ and $\bar{S}_{Cr}$. The expert's assigned prioritization classifiers $\bar{\mathbb{C}}_{C_j}$, $\bar{\mathbb{C}}_{P_j}$ and $\bar{\mathbb{C}}_{Cr_j}$ are categorizing into five uniform classes between the minimum and maximum calculated scores. The expert's assigned mitigation classifiers $\bar{\mathbb{C}}_{PAN_j}$ are assigned based on different scenarios from the survey questioner.

It is explained in chapter three that the NBC model determines the prior distributions with engineer-assigned classifiers $\mathbb{C}_{PAN_j}$, $\mathbb{C}_{C_j}$, $\mathbb{C}_{P_j}$, $\mathbb{C}_{Cr_j}$and posterior distributions with expert's assigned classifiers $\bar{\mathbb{C}}_{PAN_j}$, $\bar{\mathbb{C}}_{C_j}$, $\bar{\mathbb{C}}_{P_j}$ and $\bar{\mathbb{C}}_{Cr_j}$. The NBC generates the likelihood distributions to replicate the expert's assigned classifiers by assigning weights $\bar{\bar{W}}_{x_i}$ for variables V_{x_i}. The learning algorithm adjusts the assigned weights as many times to predict classifiers $\bar{\bar{\mathbb{C}}}_{PAN_j}$, $\bar{\bar{\mathbb{C}}}_{C_j}$, $\bar{\bar{\mathbb{C}}}_{P_j}$ and $\bar{\bar{\mathbb{C}}}_{Cr_j}$ that are close to the expert's assigned classifiers.

In this chapter, the results of the NBC with supervised learning algorithm applied on the City of London MWN database are presented in this chapter. All engineer-assigned $\mathbb{C}_{PAN_j}$, $\mathbb{C}_{C_j}$,

$\mathbb{C}_{P_j}$ and $\mathbb{C}_{Cr_j}$, expert's assigned $\bar{\mathbb{C}}_{PAN_j}$, $\bar{\mathbb{C}}_{C_j}$, $\bar{\mathbb{C}}_{P_j}$ and $\bar{\mathbb{C}}_{Cr_j}$ and model results in classifiers $\bar{\bar{\mathbb{C}}}_{PAN_j}$, $\bar{\bar{\mathbb{C}}}_{C_j}$, $\bar{\bar{\mathbb{C}}}_{P_j}$ and $\bar{\bar{\mathbb{C}}}_{Cr_j}$ are presented, compared and analyzed.

The proposed methodology is a capital activity measurement tool to evaluate the current watermain system that is disaggregated from a certain type of pipe material, location, and any other limitation. This study's results may provide a baseline that could potentially be used to benchmark the watermain performance measurement at different levels of municipal organizations. An automated scientific prioritization model based on a professional judgment that can replicate professional capital activity decisions for pipes within MWN is proposed. The next step would be having more data from another municipality to further model validation.

5.2 The Municipal Watermain Network Database

Ontario best practice (2005) recommended that water utilities keep all of their pipe condition, performance, and criticality information in ArcGIS format with their exact GPS coordination location and all its characteristics such as age, rehabilitation, break data, crossings, easement, accessibility and much other information (NRC•CNRC, 2005). London Ontario is one of few municipalities that organized their water pipe information in ArcGIS shapefile format. Two ArcGIS shapefiles were received from the Water Department at the City of London. One file contained data from MWN pipe information constructed from 1900 to date (24082 pipes) is shown in Figure B2-1 in Appendix B2. The second file contained break information that included water pipe break cause, time, type and result from 1960 to date (7341 data points), is shown in Figure B2-2 in Appendix B2. The shapefiles have spatial coordinates; therefore, these two shapefiles can be spatially matched into one shapefile with all pipe network data that included the break data. The exported shapefile is used as baseline data to build a comprehensive database consisting of all pipe information and breaks data. All additional information is added into this file according to exact spatial coordination and mapped in ArcGIS.

Using all ArcGIS base maps includes streets, watercourses, critical services locations such as hospital and fire stations, wetlands, landfills, bridges, and environmentally sensitive areas. The base maps are available for free by Esri in shapefile format. The base maps do not include water infrastructure information such as pipes location and pipe diameter. Using the base map shapefile cross-referenced with the City of London Pipe location shapefile, pipelines that are not located within the right of way and required easement are identified. Cross-reference these files and information from the City of London legal department, pipe with no easement and hard to access areas are identified in the shapefile. Binary values are identified for all crossings and locations for the criticality model. The sample binary attribute table is shown in FigureB2-5 and Figure B2-6 in Appendix B2.

The staff at the City of London provided a shapefile for critical service locations that included all critical water service locations such as hospitals, airports, schools, fire departments, etc. The critical location shapefile is shown in Figure B2-4 in Appendix B2. Spatial cross-referencing these locations with a pipe database. The crucial service locations are identified and marked in binary values in separate columns.

Watermain replacement and rehabilitation plans for capital work programs that contain total length, material, service locations and construction method for 2017 are received in excel format. This data is used to evaluate the model output and check the pipes that are chosen for replacement by the City of London experts. For water pipes that are not located within the right of way, access road information is evaluated from ArcGIS base maps. All pipes with accessibility issues are identified. Although the proposed model can take information from other software compatible with ArcGIS, the City of London did not have water pressure database information available. Instead, City of London engineers shared information regarding locations that experienced pressure loss and water pressure complaints. Based on fire department requirements, the City of London engineers also shared locations with low water pressure issues. These water pipes are marked for pressure loss issues as part of the performance model. Table 5-2 summarizes all received data from the City of London and their allocation to one of the conditions, performance, or criticality classifiers contributing to the prioritization model.

Table 5-2 Database List

Database	Type	Information	Classifier

Water Main System	GIS Shapefile of the water infrastructure	Pipe Location, Pipe Length, Pipe Diameter, Installation Date	Condition, Performance and Criticality
Water Main Breaks History	GIS point file of all break information	Break Date, Break Cause, Break Location	Condition
Critical Service Location	GIS Point file of all critical locations such as Hospitals, Fire Departments, Schools,…	Critical Service Location	Criticality
Base Maps	GIS Shapefile of City including railways, creeks and all environmentally sensitive areas	Crossing Location	Criticality
Street Map	GIS Shapefile with all public right of way information	Crossing Location, Easement availability and requirements	Criticality
Utility location	GIS shapefile of all utilities (sewer, gas, hydro,..)	Other Pipe Crossing Location	Criticality
Soil Data	GIS Shapefile on soil type and rock type provided by Ministry Environment	Soil Type, Corrosive and non-Corrosive Soil	Condition and Criticality
Pressure Zone information	GIS shapefile for all different pressure zones	Pipe Performance and water Pressure Complains	Performance
New Development Information	GIS shapefile for all new developments single house or semi	Pressure Issues	Performance
Assessed Condo Development	GIS shapefile for condo activities that are already assessed but not approved	Pressure Issues	Performance
Draft Condo Development	GIS shapefile for draft condo proposal	Pressure Issues	Performance
Registered Development	GIS shapefile for registered developments that there is no proposal	Pressure Issues	Performance
Proposed Structure	GIS shapefile that shows all proposed structure such as street furniture bus terminal or any other structure	Pressure Issues	Performance
Moratorium and Road Work	GIS shapefile included information regarding newly paved road	Road Restriction Information	Criticality
Water Complains	excel sheet that has information regarding pressure issue and area with a water pressure problem	Water Capacity and standard information - Head Loss and pressure Loss	Performance
Water Capital work information	Excel sheets that include data about all 2016 and 2017 replacement projects	new Pipe info, Pipe Diameter - Pipe Length and new Installation Date	Condition and model validation

Other Projects	Excel sheets that include information about all other projects	location of other projects or limitation for water pipe project	Criticality
Pubic Properties and Easement information	Information regarding the access roads and access availability	assess ability information	Criticality

One of the modelling complexity of the water system is that the database is not complete. They all have lots of missing information; for example, construction dates were missing for 863 pipes in the City of London database. A data quality control check is done throughout the prepared database to fill in missing data. For instance, for missing construction dates, all information is checked for any other available date from other sources, such as the water break database construction date. For 582 records construction date is found in the rehab work column and comment column. Some assumptions have been made to fill the data gaps; for example, the year 1900 is assumed for the pipes with no construction year information.

Several watermains breaks are caused by temperature or winter weather and fixed by the operation and maintenance department on an emergency basis. Records for emergency workers are not available or accessible in many municipalities. Missing information would result in maintenance work, or capital activity may be planned for a pipe that is already fixed or replaced.

Water pipe flow information and pressure information are not available by the City of London. Therefore, head-loss and pressure-loss are not calculated due to a lack of information. City engineers provided some locations with water pressure issues due to population and service increases for new developments. These identified pipes are considered for maximum pressure-loss and placed in the highest pressure-loss bins corresponding to the pipe diameter explained in Chapter 2, section 2.2.2.1.

Water complaints and water quality information is not available from the City of London. Therefore, the Water Quality column is considered as all zero as a binary value. Typically, soil toxicity, soil composition, construction, and some service de-activation on old services are not available from municipalities; this is the same from London's City. All available data combined into a comprehensive database included all information about all water pipes in the City of London water network database recommended by best practice (NRC•CNRC, 2005). The final complete attribute table columns and their information are presented in detail in Appendix B1. The City of London water network data and pipes attribute histograms are shown in Appendix B3.

For the purpose of NBC with a supervised learning algorithm, it was assumed all variables are independent and do not correlate with each other. The NBC is mainly used for real-life problems, and most variables in real-life examples are not 100% independent. To check the correlations of the variables, Table 5-3 is prepared to show the correlations among the variable values for the City of London data.

Table 5-3 All Variables Correlation Matrix

	RSL	MI	TB	TB5Yrs	CLS	PL	WQ	D	L	AC
RSL	1									
MI	0.689024	1								
TB	0.199216	0.220238	1							
TB5Yrs	0.097649	0.109966	0.552198	1						
CLS	0.484964	0.303408	0.094694	0.042273	1					
PL	0.004468	0.026339	0.045178	0.031292	0.129934	1				
WQ	NA	NA	NA	NA	NA	NA	1			
D	-0.01783	-0.0972	-0.05777	-0.03094	-0.19638	-0.12138	NA	1		
L	-0.00398	0.038458	-0.01984	0.010218	-0.01315	-0.00243	NA	0.066466	1	
AC	0.064415	0.021964	0.030099	0.027678	0.04345	0.025346	NA	0.008942	0.021384	1

5.3 Model Application

This section explains the classification models. They used the prior distributions from the municipal engineer-assigned variable values and posterior distributions from the expert's assigned variable values to adjust the likelihood distributions with generating weights for all variables and replicate the expert's assigned classifiers.

This section explains the two-level classification models. The first level or prioritization model classifies all pipes for condition $\mathbb{C}_{C_j}$, performance $\mathbb{C}_{P_j}$, and criticality $\mathbb{C}_{Cr_j}$,. The second level of mitigation classifier would use all engineer-assigned variable values V_{X_i} to predict mitigation classifiers $\bar{\bar{\mathbb{C}}}_{PAN_j}$as close as possible to expert assigned mitigation classes $\bar{\mathbb{C}}_{PAN_j}$.

5.3.1 The Prioritization Model

The prioritization model uses engineer-assigned classifiers $\mathbb{C}_{C_j}$, $\mathbb{C}_{P_j}$ and $\mathbb{C}_{Cr_j}$ to generate prior distributions. The prioritization model uses target classifiers $\bar{\mathbb{C}}_{C_j}$, $\bar{\mathbb{C}}_{P_j}$ and $\bar{\mathbb{C}}_{Cr_j}$ to generate posterior distributions. The prioritization model adjust model assigned weights $\bar{\bar{W}}_{x_i}$ to predict the classifiers $\bar{\bar{\mathbb{C}}}_{C_j}$, $\bar{\bar{\mathbb{C}}}_{P_j}$ and $\bar{\bar{\mathbb{C}}}_{Cr_j}$with high accuracy comparing with target classifiers.

The NBC model classifies every pipe within the MWN according to its condition and performance to five uniform classes $\bar{\bar{\mathbb{C}}}_{C_j}$, $\bar{\bar{\mathbb{C}}}_{P_j}$ (1-VERY GOOD, 2-GOOD, 3-MODERATE, 4-POOR, and 5-VERY POOR) and criticality to five classes $\bar{\bar{\mathbb{C}}}_{Cr_j}$ (1-VERY LOW, 2-MODERATELY LOW, 3- MEDIUM, 4- MODERATELY HIGH and 5 – VERY HIGH). Therefore, each pipe segment is assigned a classifier consisting of a "descriptor" and an "enumerated value" in the interval of one to five.

5.3.1.1 Condition

There are four attributes considered in the condition model V_{RSL_i}, V_{TB_i}, V_{BLFVY_1}, and V_{MI_i} each attribute has two sets of variable values. The municipal engineer assigns the first set as the initial variable value V_{X_i}, and the second set is assigned by the expert $\bar{V}_{X_i}$ that is captured from the survey questioner. All values are presented in Table 5-4. All variable values and scores in the ArcGIS attribute table are shown in Figure B2-9 in Appendix B2.

The NBC links all variable bins to target classes assigned by experts as part of the survey by calculating each variable's probability of appearance value in every class. Figure 5-1 shows the condition variables histograms. The supervised machine learning will repeat this step until the model can predict a class as close as possible. The condition model is capable of replicating target classes with up to 78 percent accuracy Figure B2-10 in Appendix B2. It means the condition model is able to predict professional opinion correctly, 78 percent of the time. All classes are populated in a separate column in the ArcGIS attribute table. The ArcGIS attribute tables are shown in, Figure B2-8 and Figure B2-9 in Appendix B2.

Table 5-4 Variable Values for Condition Model

Remaining Service Life (Year)	$RSL \leq 15\ years$	$15 < RSL \leq 30\ years$	$30 < RSL \leq 50\ years$	$RSL > 50\ years$
Municipal Engineer Assigned	$V_{RSL_1} = 15$	$V_{RSL_2} = 10$	$V_{RSL_3} = 5$	$V_{RSL_4} = 0$
Expert Assigned (Target)	$\bar{V}_{RSL_{1,}=}$ 10.5	$\bar{V}_{RSL_2} = 6.7$	$\bar{V}_{RSL_3} = 5.1$	$\bar{V}_{RSL} = 0$
Total Number of Breaks	$TB \geq 9$	$8 \geq TB \geq 5$	$4 \geq TB \geq 1$	TB = 0
Municipal Engineer Assigned	$V_{TB_1} = 15$	$V_{TB_2} = 10$	$V_{TB_3} = 5$	$V_{TB_1} = 0$
Expert Assigned (Target)	$\bar{V}_{TB_1} = 13.4$	$\bar{V}_{TB_2} = 11.2$	$\bar{V}_{TB_3} = 7.2$	$\bar{V}_{TB_4} = 5.4$
Breaks in last 5 years	$TB_{5yrs} \geq 5$	$4 \geq TB_{5yrs} \geq 3$	$2 \geq TB_{5yrs} \geq 1$	$TB_{5yrs} = 0$
Municipal Engineer Assigned	$V_{BLFVY_1} = 15$	$V_{BLFVY_2} = 10$	$V_{BLFVY_3} = 5$	$V_{BLFVY_4} = 0$
Expert Assigned (Target)	$\bar{V}_{BLFVY_1} = 13.4$	$\bar{V}_{BLFVY_2} = 11.2$	$\bar{V}_{BLFVY_3} = 7.2$	$\bar{V}_{BLFVY_4} = 5.4$
Total Number of Breaks	$MI \leq 0.01$	$1 < MI \leq 0.05$	$MI > 0.05$	
Municipal Engineer Assigned	$V_{MI_1} = 5$	$V_{MI_2} = 10$	$V_{MI_3} = 15$	
Expert Assigned (Target)	$\bar{V}_{MI_1} = 5$	$\bar{V}_{MI_2} = 10$	$\bar{V}_{MI_3} = 15$	

The condition model levels are classified into five categories, as shown in Table 5-5. For example, most pipes with low condition scores S_{C_i} and $\bar{S}_{C_i}$ are in relatively good condition. According to survey results, experts believed that based on the number of breaks and age, the City of London pipes are in relatively good condition in classes $\bar{\mathbb{C}}_{C_1} = 1$ and $\bar{\mathbb{C}}_{C_2} = 2$. This is professional judgement, and it varies by different engineers and different municipalities. The expert agreed that only very few pipes are in $\bar{\bar{\mathbb{C}}}_{C_5}$ = VERY POOR condition class five. These results are clearly shown in condition histogram Figure 5-2. Thus, most pipes in City of London MWN are generally in $\bar{\bar{\mathbb{C}}}_{C_1}$ = VERY GOOD and $\bar{\bar{\mathbb{C}}}_{C_2}$ = GOOD condition classes making maintenance decisions or prioritizing maintenance decisions require further information about these pipes, such as performance and criticality measurements.

Table 5-5 Condition Classes

Condition Categories

S_{C_i}	$\bar{S}_{C_i}$	Classifiers $\mathbb{C}_{C_j}$, $\bar{\mathbb{C}}_{C_j}$ and $\bar{\bar{\mathbb{C}}}_{C_j}$		Relative Prioritization Order
0 - 10	0 – 17.9	VERY GOOD	1	A pipe is in VERY GOOD condition. No mitigation is required.
10 - 20	17.9 – 24.9	GOOD	2	A pipe is in GOOD condition. No mitigation is required.
20 – 30	24.9– 32	MODERATE	3	A pipe is in MODERATE condition and should be prioritized for mitigation.
30 – 40	32 – 39	POOR	4	A pipe is in POOR condition and should be prioritized for mitigation.
40 – 50	39 – 46.1	VERY POOR	5	A pipe is in VERY POOR condition and requires immediate mitigation.

The condition model's result on the ArcGIS interface is shown in Figure B2-14 in Appendix B2. These colour-coded results highlight all pipes according to their physical condition. This model identifies pipes that require more attention within the entire system.

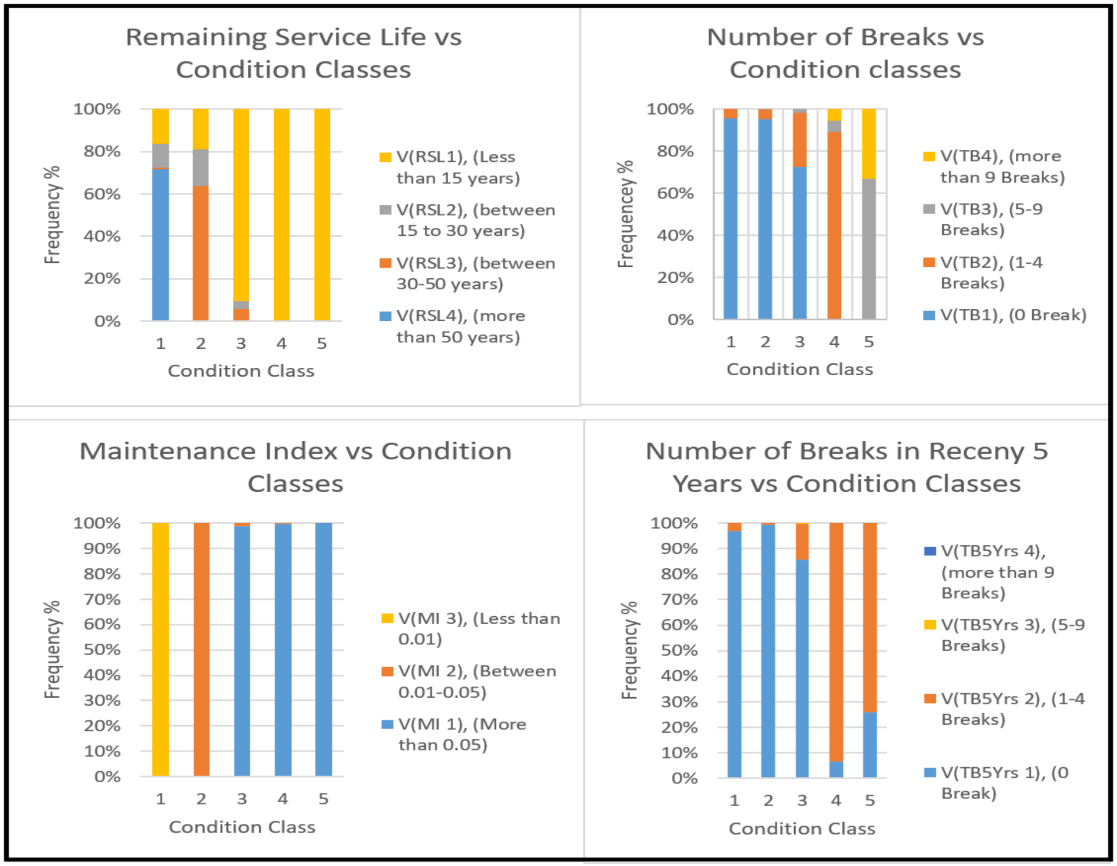

Figure 5-1 Condition Variables PDFs

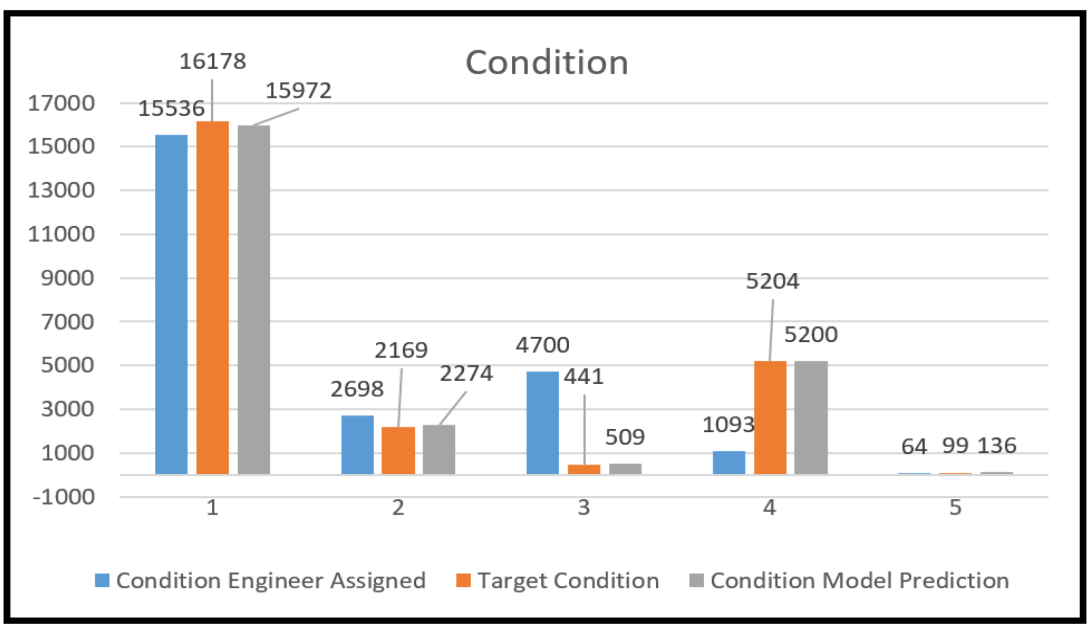

Figure 5-2 Condition Result Histogram

5.3.1.2 Performance

The City of London has very limited pipe performance information. They only identified a few areas with pressure-related issues, including all new and proposed development plan areas. These areas are identified by spatially cross-referencing new developments shapefile and the pressure issue file. Variables chosen for performance can be different at each municipality based on their needs. There are three attributes considered in the performance model V_{PL_i}, V_{WQ_i}, and V_{CLS_i} each attribute has two sets of variable values. The municipal engineer-assigns V_{X_i} the expert assigns the first set as the initial variable value and the second set $\bar{V}_{X_i}$that is captured from the survey questioner. All values are presented in Table 5-6.

Table 5-6 Variable Values for Performance Model

Pressure Loss	0-600mm pipe diameter	PL>5.0	2.0<PL<5.0	PL<2.0
	pipes larger than 600mm diameter	PL>2.5	1.5<PL<2.5	PL<1.5
Municipal Engineer Assigned		$V_{PL_1} = 15$	$V_{PL_2} = 5$	$V_{PL_3} = 0$
Expert Assigned (Target)		$\bar{V}_{PL_1} = 15$	$\bar{V}_{PL_2} = 5$	$\bar{V}_{PL_3} = 0$
Water Quality		Poor Water Quality	Good Water Quality	
Municipal Engineer Assigned		$V_{WQ_1} = 15$	$V_{WQ_2} = 0$	
Expert Assigned (Target)		$\bar{V}_{WQ_1} = 10.7$	$\bar{V}_{WQ_2} = 0$	
Conformance with Latest Standard		Conforming with the Latest Standard	Not Conforming with the latest Standard	
Municipal Engineer Assigned		$V_{CLS_1} = 0$	$V_{CLS_2} = 15$	
Expert Assigned (Target)		$\bar{V}_{CLS_1} = 0$	$\bar{V}_{CLS_2} = 9.5$	

Each municipality has a unique water system and requirements; for example, in the City of London, pipes of any pipe smaller than 150mm diameter do not conform to current standards and must be changed. All variable values are populated in ArcGIS for this model, shown in Figure B2-13 and Figure B2-14 in Appendix B2.

A few variables have binary values in the prioritization model. The Naïve Bayes classifier with a supervised learning algorithm is well-suited to utilize binary data. Even when the variable value for any attribute is not available, the Naïve Bayes classifier with a supervised learning algorithm would be able to use other attributes and variable values to predict the classifier $\bar{\bar{\mathbb{C}}}_{P_j}$. In the City of London database, the performance model predicts a performance class $\bar{\bar{\mathbb{C}}}_{P_j}$ that is very close to the class that the expert may assign with very high (99%).

The performance model levels are classified into five categories, as shown in Table 5-7 According to survey results, experts believed the City of London pipes perform well, attribute them into classes $\bar{\bar{\mathbb{C}}}_{P_1}$= 1 and $\bar{\bar{\mathbb{C}}}_{P_2}$=2. Although the engineer-assigned classifiers $\mathbb{C}_{P_j}$for the City of London is $\mathbb{C}_{P_1}$ =1 and $\mathbb{C}_{P_3}$=3. The engineers believed the City of London pipes mostly exhibit $\mathbb{C}_{P_3}$= MODERATE performance, whereas the experts believe the City of London pipes exhibits $\bar{\mathbb{C}}_{P_2}$= GOOD performance. The reason for this discrepancy is mostly the lack of data for this model.

Using this model, all problematic pipes can be identified and marked to be considered for future investigation. Also, performance issues would help identify water pressure and capacity issues important for the building permit department and develop any condo proposal or high-rise applications on top of the hydraulic modelling or any additional requirements. This additional information would be very valuable information to plan and prioritize capital activities.

Figure B2-15 in Appendix B2 shows the ArcGIS interface that categorizes all pipes in five different classifiers with different colours. This model identifies pipes that are not performing well in the entire water system. In addition to physical pipe conditions, a performance indicator is crucial to prioritize linear infrastructure capital activities.

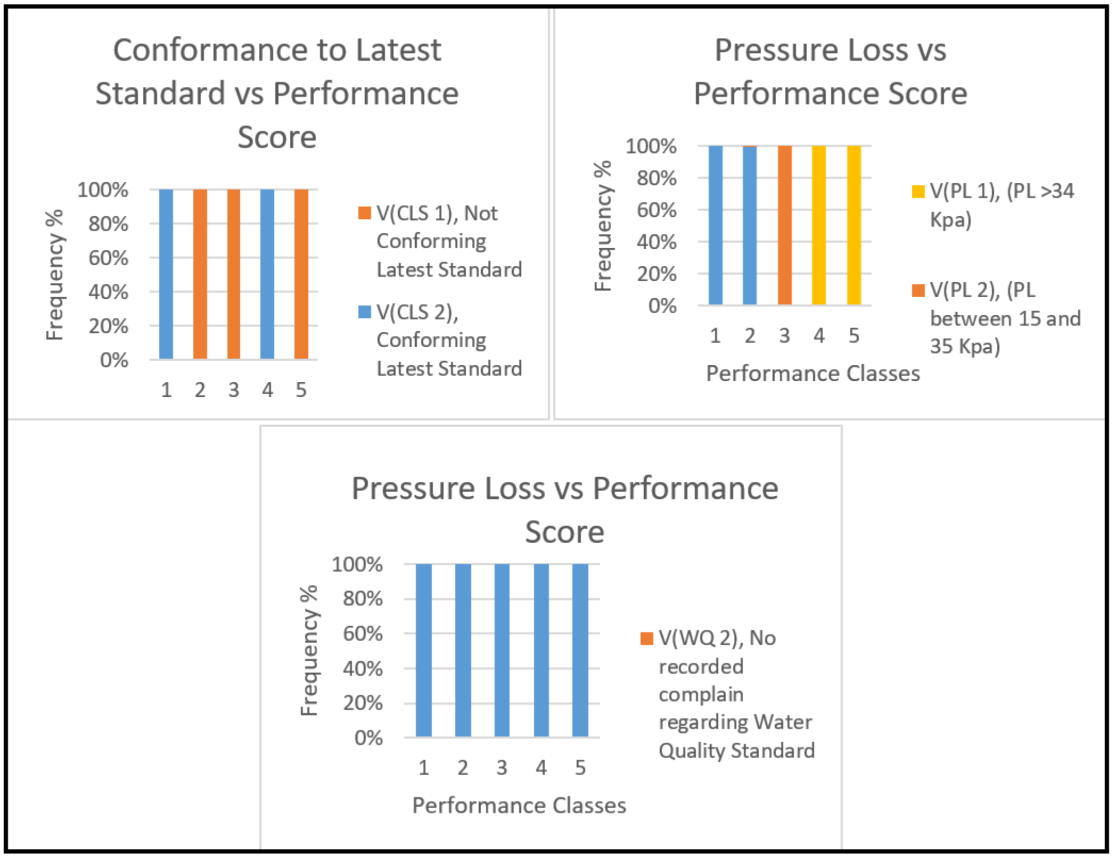

Figure 5-3 Performance Variables PDFs

Table 5-7 Performance Classes

Performance Categories				
S_{P_i}	$\bar{S}_{P_i}$	Classifiers $\mathbb{C}_{P_j}$, $\bar{\mathbb{C}}_{P_j}$ and $\bar{\bar{\mathbb{C}}}_{P_j}$		Relative Prioritization Order
0-6	0-4.9	VERY GOOD	1	Pipe exhibits a VERY GOOD performance. No mitigation is required.
6-12	4.9-9.8	GOOD	2	Pipe exhibits GOOD performance. No mitigation is required.
12-18	9.8-14.7	MODERATE	3	Pipe exhibits MODERATE performance and should be prioritized for mitigation.
18-24	14.7-19.6	POOR	4	Pipe exhibits POOR performance and should be prioritized for mitigation.
24-30	19.6-24.5	VERY POOR	5	Pipe exhibits VERY POOR performance and requires immediate mitigation

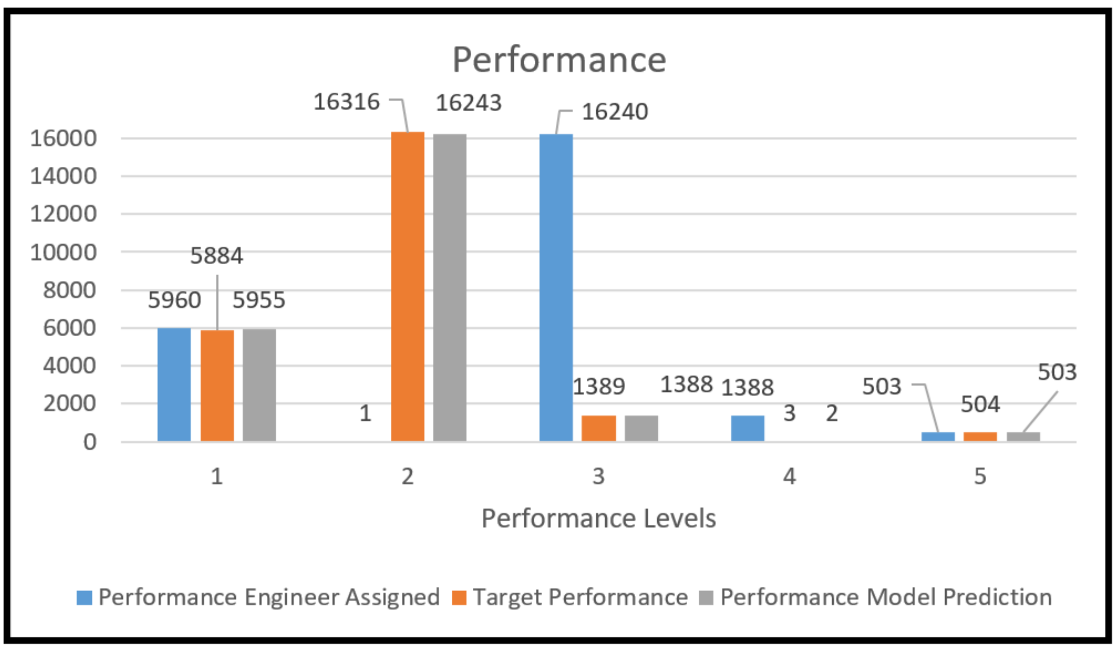

Figure 5-4 performance Result Histogram

5.3.1.3 Criticality

The criticality of each pipe is measured based on the consequence of failure. For example, failure impacts for large diameter pipes are greater than for small diameter pipes. Failure for pipes providing service to critical locations such as hospitals or airports is more critical than a small pipe that provides service to few residential properties. Pipes passing or crossing environmentally sensitive areas without an access road or easement have a very high failure impact relative to other pipes. Therefore, these pipes are identified, and data are populated in the ArcGIS attribute table in binary format, as shown in Figure B2-16 and Figure B2-17 Appendix B2. Due to each city's unique geographic location, the list of criticality variables may differ between municipalities. For the City of London, there are three attributes considered in the criticality model V_{D_i}, V_L, and V_{AC_i} each attribute has two sets of variable values. The municipal engineer assigns the first set as the initial variable value V_{X_i}, and the second set is assigned by the expert $\bar{V}_{X_i}$ that is captured from the survey questioner. All values are presented in Table 5-8.

Table 5-8 Variable Values for Criticality Model

Pipe Diameter	$D > 750\ mm$	$600\ mm < D \leq 750\ mm$	$300\ mm < D \leq 600\ mm$	$D \leq 300\ mm$
Municipal Engineer Assigned	$V_{D_1} = 15$	$V_{D_2} = 10$	$V_{D_3} = 5$	$V_{D_4} = 0$
Expert Assigned (Target)	$\bar{V}_{D_{1,}} = 11.8$	$\bar{V}_{D_2} = 10.9$	$\bar{V}_{D_3} = 9.8$	$\bar{V}_{D_4} = 7.8$
Pipe Location	Located within ESPA	Located outside ESPA		
Municipal Engineer Assigned	$V_{L_1} = 15$	$V_{L_2} = 0$		
Expert Assigned (Target)	$\bar{V}_{L_1} = 11.2$	$\bar{V}_{L_2} = 0$		
Pipe Accessibility	NOT Accessible	Accessible		
Municipal Engineer Assigned	$V_{AC_1} = 15$	$V_{AC_2} = 0$		
Expert Assigned (Target)	$\bar{V}_{AC_1} = 9$	$\bar{V}_{AC_2} = 0$		

The NBC model identified critical pipes based on engineering judgement that is captured via survey for all pipes through the City of London water system. Figure 5-5 presents all criticality attributes pdfs. The supervised learning algorithm is able to learn professional opinion from target criticality levels up $\bar{\mathbb{C}}_{Cr_j}$to 90 percent accuracy. Figure B2-10 in Appendix B2 shows the model accuracy on the python interface in ArcGIS. This model, like the other sections, categorizes the criticality scores into five classifiers.

The criticality model levels $\bar{\bar{\mathbb{C}}}_{Cr_j}$are classified into five categories, as shown in Table 5-9 According to experts, a very small number of pipes in the City of London are considered $\bar{\bar{\mathbb{C}}}_{Cr_4}$= MODERATELY HIGH and $\bar{\bar{\mathbb{C}}}_{Cr_5}$= VERY HIGH criticality class. Using this model, all critical pipes are identified to be considered as higher priorities for capital activities. Figure B2-18 in Appendix B2 shows City of London Water System criticality model results.

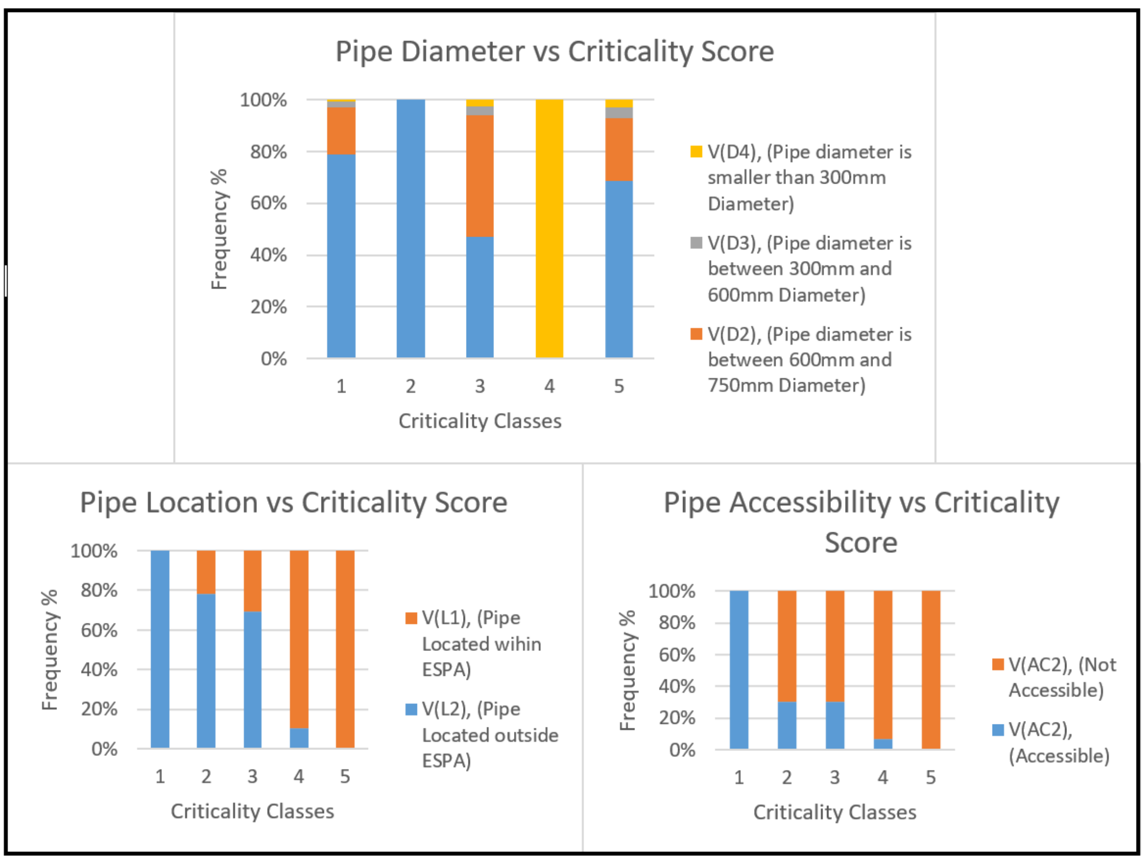

Figure 5-5 Criticality Variables PDFs

Table 5-9 Criticality Classes

Criticality Categories				
S_{Cr_i}	$\bar{S}_{Cr_i}$	Classifiers $\mathbb{C}_{Cr_j}$, $\bar{\mathbb{C}}_{Cr_j}$ and $\bar{\bar{\mathbb{C}}}_{Cr_j}$		Relative Prioritization Order
0 - 9	0 – 12.1	VERY LOW	1	A Pipe exhibits VERY LOW criticality.
9 – 18	12.1 – 17.1	MODERATELY LOW	2	A pipe is in MODERATELY LOW criticality.
18 – 27	17.1 - 22	MEDIUM	3	A Pipe exhibits MEDIUM criticality.
27 – 36	22 - 27	MODERATELY HIGH	4	A Pipe exhibits MODERATELY HIGH criticality.
36 – 45	27 - 32	VERY HIGH	5	A pipe has VERY HIGH criticality.

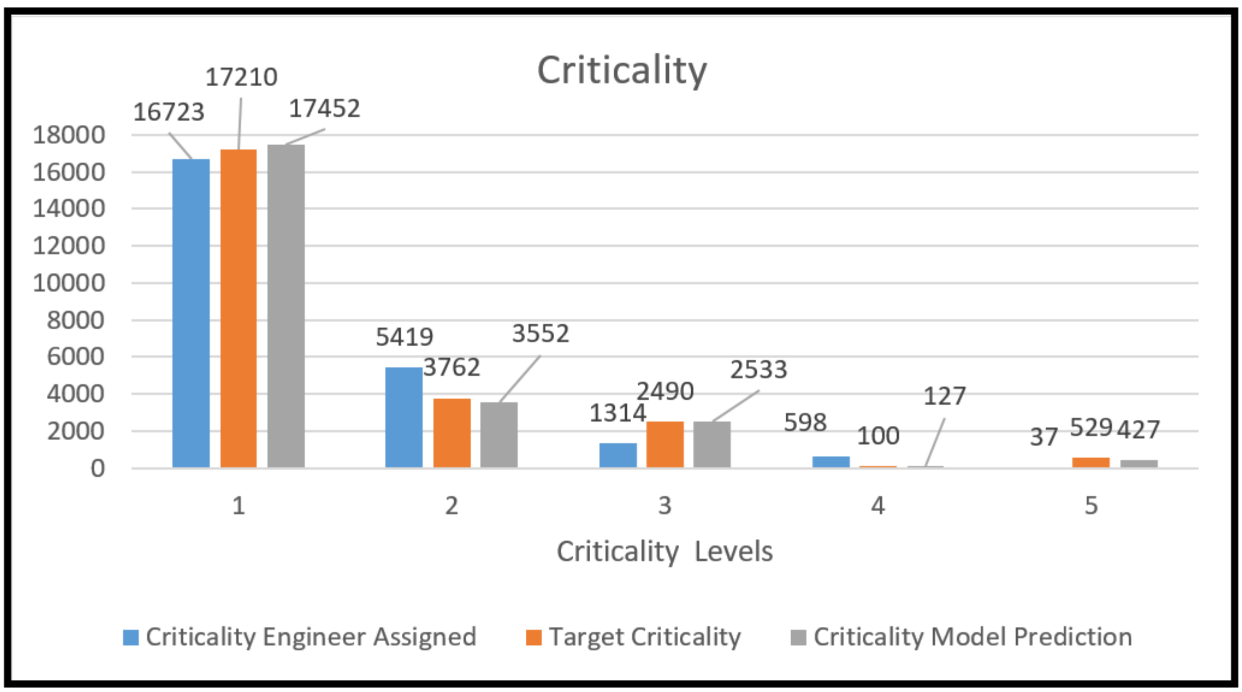

Figure 5-6 Criticality Result Histogram

5.3.2 The Mitigation Model

The second level model classifies all water pipes for mitigating the capital works activities. The PAN is the sum of all engineer-assigned condition, performance, and criticality scores S_C, S_P and S_{Cr} multiplied by their respective weight W_C, W_P and W_{Cr}. PAN is used to rank pipes or "prioritize" them for a selected mitigation activity $\mathbb{C}_{PAN_j}$. The engineer-assigned mitigation classifiers $\mathbb{C}_{PAN_j}$ is assigned uniformly based on the minimum and maximum PAN into four categories which are called mitigation classes. Table 5-10 shows PAN classifier boundaries.

Table 5-10 PAN Scores and Levels

Mitigation Categories		
PAN	Relative Prioritization Order	Classifiers $\mathbb{C}_{PAN_j}$
0 - 312	DO NOTHING	1
312 - 475	RELINE-REHAB using trenchless technology	2
475 - 637	REPLACE the pipe with one of the same size	3
637 - 800	replace and UP-SIZE the Pipe with one of a larger diameter.	4

The mitigation model uses engineer-assigned PAN classifiers $\mathbb{C}_{PAN_j}$ to create prior distributions and experts assigned mitigation classifiers or target classifiers $\bar{\mathbb{C}}_{PAN_j}$to generate posterior distributions. Figure B2-20 in Appendix B2 shows the ArcGIS interface showing the City of London PAN. Target classifiers $\bar{\mathbb{C}}_{PAN_j}$ are the outcome of sample water pipe scenarios from the survey. The NBC generate likelihood distributions to create weights $\bar{\bar{W}}_{X_i}$for all variable values, engineer-assigned variable values $V_{X_i}$to classify the mitigation results into four different classes $\bar{\bar{\mathbb{C}}}_{PAN_j}$(1- DO NOTHING, 2- RELINE - REHAB 3- REPLACE with the same pipe size, and 4-UP-SIZE or replace with larger pipe size categories). The supervised learning algorithm, through the training process, adjust the weights $\bar{\bar{W}}_{X_i}$to increase the accuracy of the model predicted mitigation classes $\bar{\bar{\mathbb{C}}}_{PAN_j}$ to target classes $\bar{\mathbb{C}}_{PAN_j}$. The mitigation model is able to automate assigning a capital works activity to every pipe within the MWN that are based on each pipe target condition, performance and criticality classes $\bar{\mathbb{C}}_{C_j}$, $\bar{\mathbb{C}}_{P_j}$ and $\bar{\mathbb{C}}_{Cr_j}$.

The mitigation model assigned $\bar{\bar{\mathbb{C}}}_{PAN_1}$= DO NOTHING classifier for pipes with condition classifiers $\bar{\bar{\mathbb{C}}}_{C_j}$ ∈ (VERY GOOD and GOOD) , performance classifiers $\bar{\bar{\mathbb{C}}}_{P_j}$ ∈ (VERY GOOD and GOOD) and criticality classifiers $\bar{\bar{\mathbb{C}}}_{Cr_j}$ ∈ (VERY LOW, MODERATELY LOW, MEDIUM, MODERATELY HIGH and VERY HIGH). The NBC supervised learning algorithm assigned $\bar{\bar{\mathbb{C}}}_{PAN_2}$= RELINE-REHAB. Pipe classified by the NBC supervised learning algorithm in this classifier belongs to $\bar{\bar{\mathbb{C}}}_{C_j}$ ∈ (GOOD, MODERATE, POOR and VERY POOR) condition classes and $\bar{\bar{\mathbb{C}}}_{P_j}$ ∈ (VERY GOOD, GOOD, MODERATE and POOR) performance classes with criticality class $\bar{\bar{\mathbb{C}}}_{Cr_j}$ ∈ (VERY LOW, MODERATELY LOW, MEDIUM and MODERATELY HIGH). The criticality classifier would prioritize the capital work.

The NBC supervised learning algorithm assigns $\bar{\bar{\mathbb{C}}}_{PAN_3}$= REPLACE to pipes with condition classifiers $\bar{\bar{\mathbb{C}}}_{C_j}$ ∈ (MODERATE, POOR or VERY POOR) and performance classifiers as $\bar{\bar{\mathbb{C}}}_{P_j}$ ∈ (GOOD, MODERATE, POOR and VERY POOR). Pipes with REPLACE mitigation class may have any criticality classifier $\bar{\bar{\mathbb{C}}}_{Cr_j}$ ∈ (VERY LOW, MODERATELY LOW, MEDIUM, MODERATELY HIGH or VERY HIGH). The criticality classifier would prioritize the replacement program. For example, pipes with $\bar{\bar{\mathbb{C}}}_{Cr_5}$= VERY HIGH criticality would prioritize over Pipe's $\bar{\bar{\mathbb{C}}}_{Cr_1}$= VERY LOW criticality class. The NBC supervised learning algorithm classifies pipes with performance issues in $\bar{\bar{\mathbb{C}}}_{PAN_4}$= UP-SIZE class. This classifier is assigned when conditions classifier $\bar{\bar{\mathbb{C}}}_{C_j}$ ∈ (POOR or VERY POOR), performance classifiers are $\bar{\bar{\mathbb{C}}}_{P_j}$ ∈ (MEDIUM, POOR or VERY POOR) and criticality classifiers are $\bar{\bar{\mathbb{C}}}_{Cr_j}$ ∈ (MEDIUM, MODERATELY HIGH or VERY HIGH). Figure 5-7 summarizes the classification rules as explained.

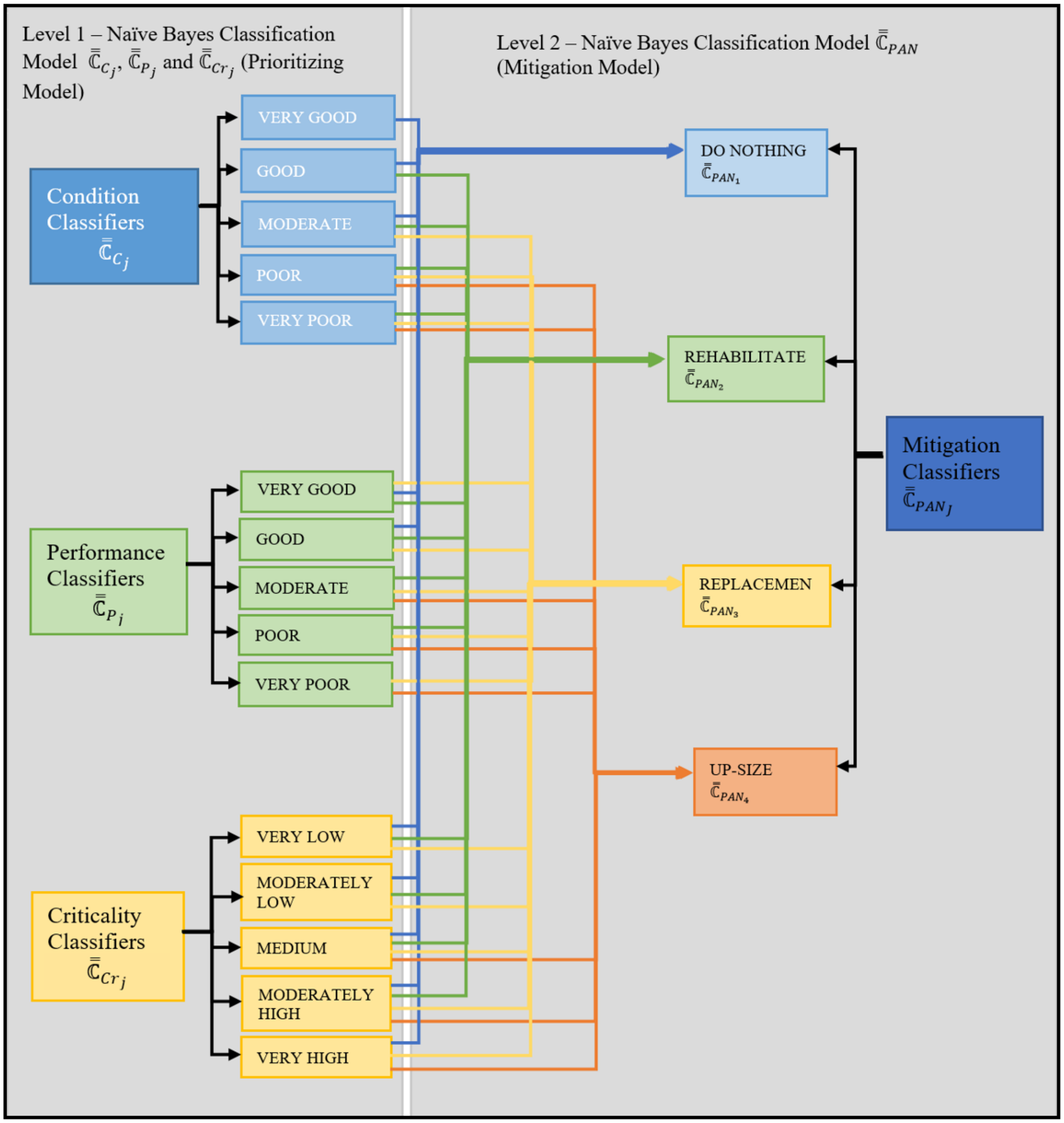

Figure 5-7 Survey Result Classifications

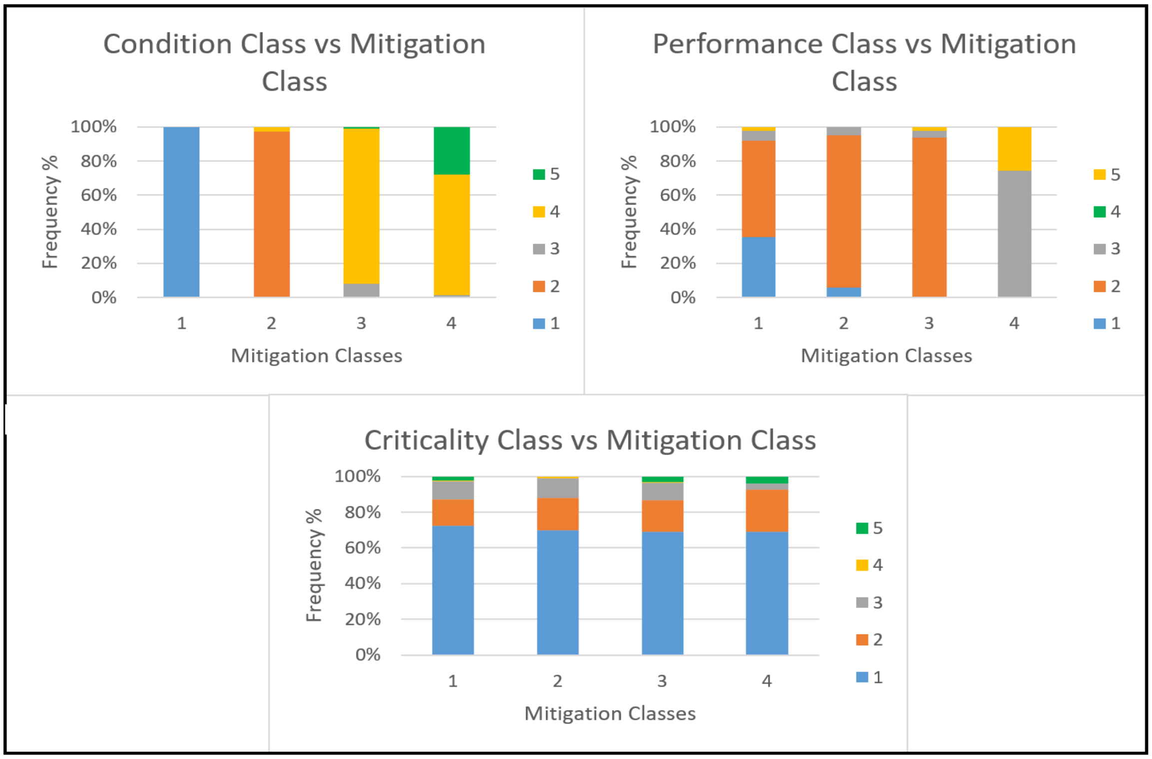

Figure 5-8 Prioritization Classes vs Mitigation Class

The NBC supervised learning model is applied to the City of London MWN. The mitigation decisions reflecting the expert's classifiers are achieved with relatively high accuracy of 88 percent. Figure 5-8 summarizes the frequency of appearance of each prioritization class in each mitigation class. Figure 5-8 shows higher condition and performance classes $\bar{\bar{\mathbb{C}}}_{C_j}$ and $\bar{\bar{\mathbb{C}}}_{P_j}$ appeared in high mitigation classes $\bar{\bar{\mathbb{C}}}_{PAN_j}$, but all criticality classes $\bar{\bar{\mathbb{C}}}_{Cr_j}$ appeared the same on all mitigation classes $\bar{\bar{\mathbb{C}}}_{PAN_j}$. Therefore, pipes with condition and performance issues are identified for capital activities, and the pipe's criticality classifier would make the capital activity more urgent. All results are populated in ArcGIS attribute data for each pipe. Figure B2-21 in Appendix B2 shows all mitigation model results in the ArcGIS interface.

All variables V_{X_i} from prioritization, models are used in the mitigation model. Figure 5-9 shows all probability in mitigation classifier $\bar{\bar{\mathbb{C}}}_{PAN_j}$. This result confirms that prioritizing capital activities requires much more information than pipe conditions. A performance or criticality attribute may change the mitigation classification of a given pipe segment. This is the most important shortcoming from the available literature that primarily focused on pipes' physical condition for capital activity decisions.

The mitigation distribution histogram in Figure 5-10 shows most pipes that appeared in class $\bar{\bar{\mathbb{C}}}_{PAN_1}$= 1 are required to DO NOTHING. A few pipes are in class four require $\bar{\bar{\mathbb{C}}}_{PAN_4}$ UP-SIZE, and there are pipes in class two $\bar{\bar{\mathbb{C}}}_{PAN_2}$= REHABILITATION and three $\bar{\bar{\mathbb{C}}}_{PAN_3} =$ REPLACEMENT. In addition to mitigation solutions, condition, performance and criticality model would prioritize the required maintenance activity. For example, a pipe that requires upsizing classifies $\bar{\bar{\mathbb{C}}}_{PAN_4}$as exhibiting class four condition $\bar{\bar{\mathbb{C}}}_{C_4}$and class four criticality $\bar{\bar{\mathbb{C}}}_{Cr_4}$should be given a higher priority than another pipe that requires upsizing $\bar{\bar{\mathbb{C}}}_{PAN_4}$with class four condition $\bar{\bar{\mathbb{C}}}_{C_4}$and class one criticality $\bar{\bar{\mathbb{C}}}_{Cr_1}$.

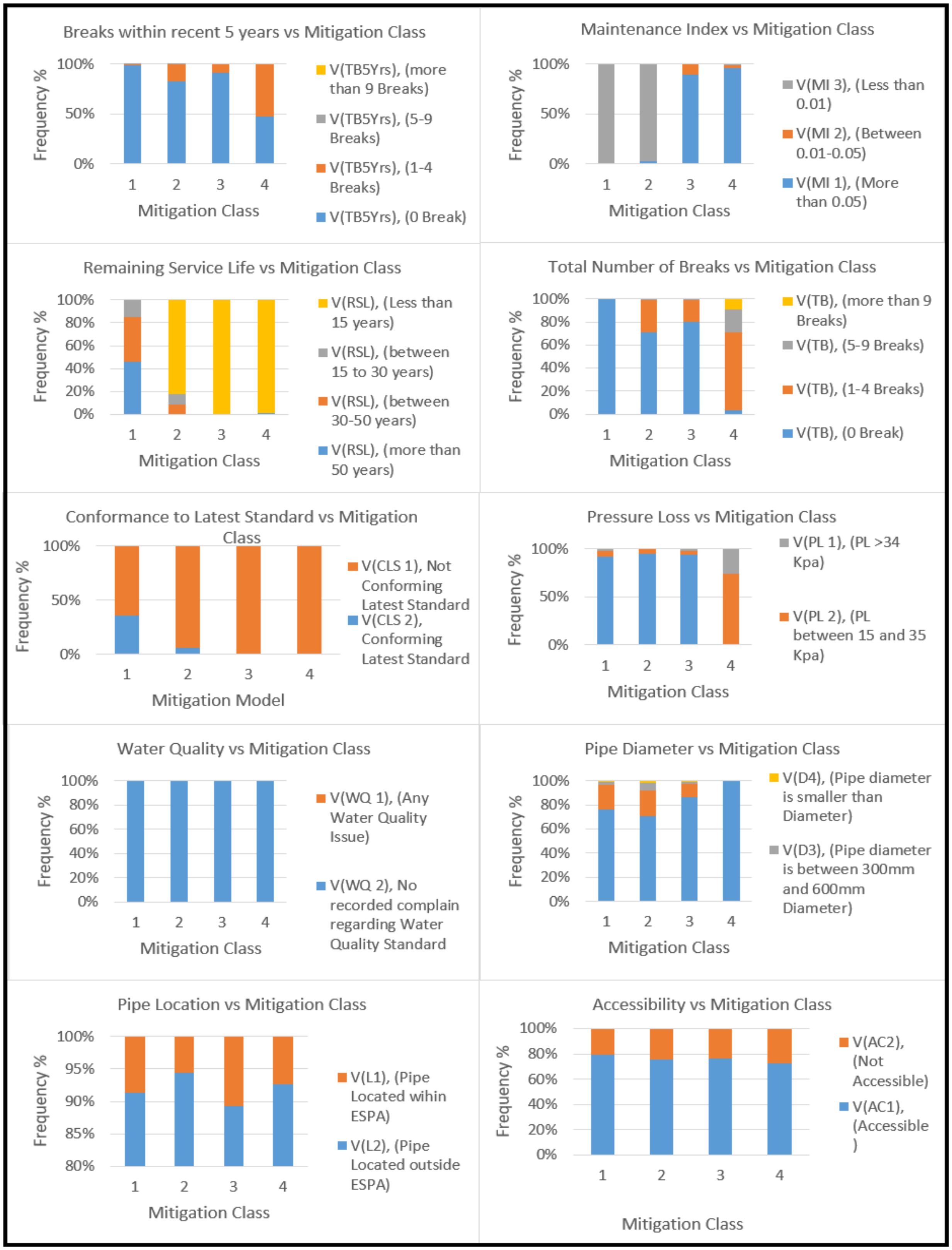

Figure 5-9 Mitigation Model Variables

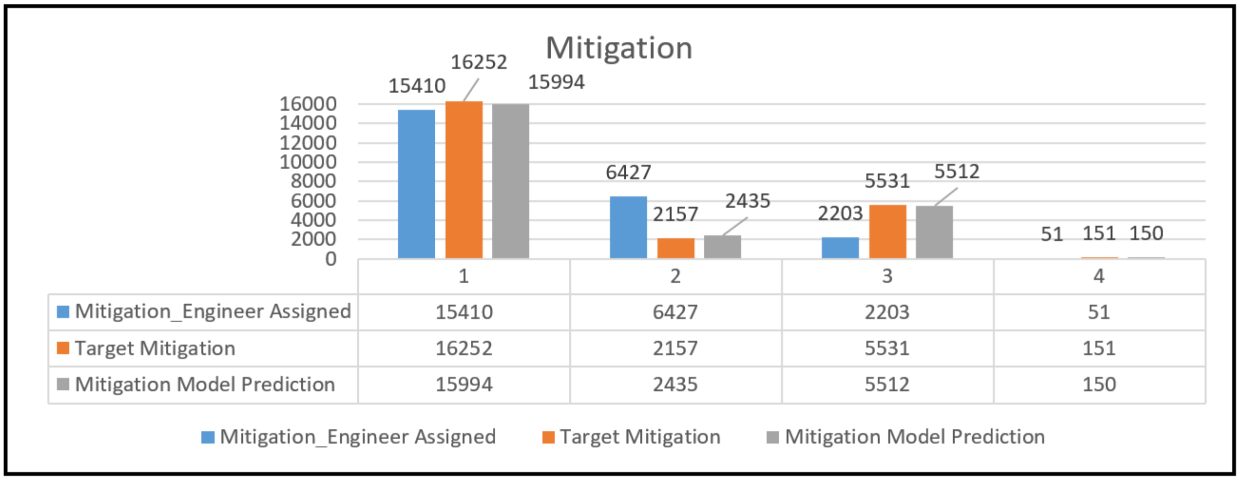

Figure 5-10 Mitigation Results Histogram

5.4 Verification Exercises

This section presents and compares all engineer-assigned classifiers $\mathbb{C}_{C_j}$, $\mathbb{C}_{P_j}$, $\mathbb{C}_{Cr_j}$ and $\mathbb{C}_{PAN_j}$ experts assigned classifiers (target classifiers) $\bar{\mathbb{C}}_{C_j}$, $\bar{\mathbb{C}}_{P_j}$, $\bar{\mathbb{C}}_{Cr_j}$ and $\bar{\mathbb{C}}_{PAN_j}$ and all model predicted classifiers $\bar{\bar{\mathbb{C}}}_{C_j}$, $\bar{\bar{\mathbb{C}}}_{P_j}$, $\bar{\bar{\mathbb{C}}}_{Cr_j}$ and $\bar{\bar{\mathbb{C}}}_{PAN_j}$. The mitigation model results and how municipalities may use the PAN, condition, performance and criticality classifiers to make capital project decisions are presented.

The PAN calculated by municipal engineer-assigned variable values would set the priority of the assigned mitigation. For example, using MWN data and apply the NBC model; the result would be bins that include many pipes for $\bar{\bar{\mathbb{C}}}_{PAN_2}$ = RELINE-REHAB or $\bar{\bar{\mathbb{C}}}_{PAN_3}$ = REPLACEMENT, but there are restrictions such as time and resources, which pipe has to go first. The prioritization decision would be made by the municipal engineer looking at the criticality classifier $\bar{\bar{\mathbb{C}}}_{Cr_j}$ and PAN. The higher criticality classes would be prioritized over lower priority classes. The larger the PAN value is, the higher the pipe priority would be. This section explains the automated mitigation solution assigned using NBC supervised learning algorithm and prioritizing process using all prioritization classifiers and PAN.

5.4.1 DO NOTHING Mitigation Classification

To demonstrate this methodology using the City of London database, a sample pipe is chosen for each mitigation classifier $\bar{\bar{\mathbb{C}}}_{PAN_j}$. There are 15994 pipe sections in the City of London that meet the criterion for this classifier. Figure 5-11shows the locations of these pipes.

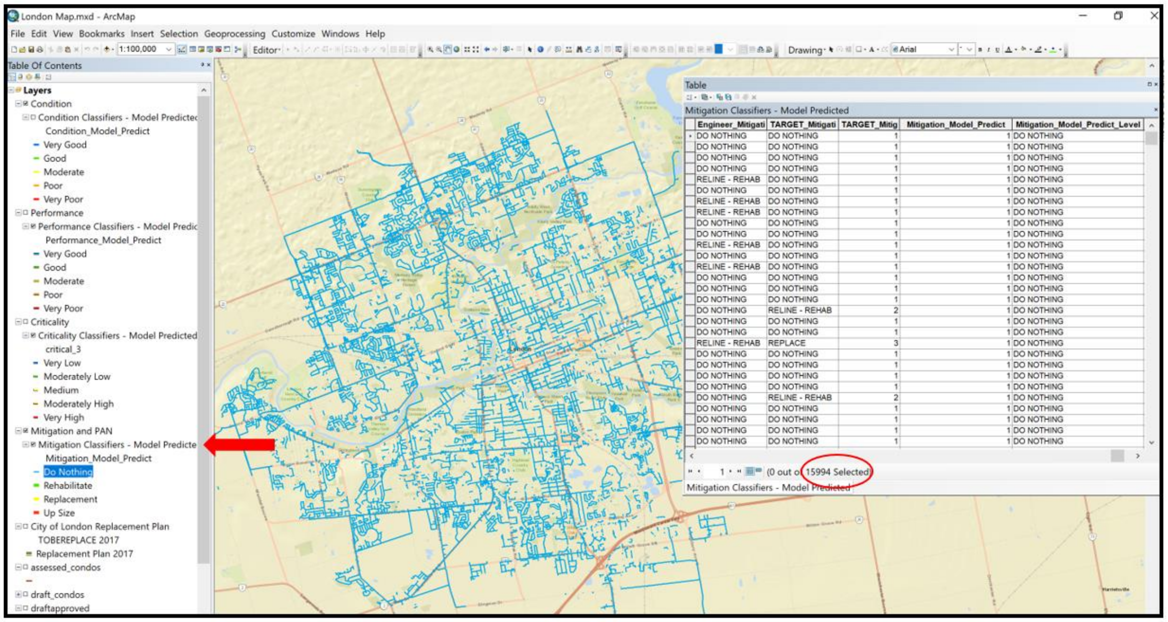

Figure 5-11 DO NOTHING Mitigation Result

For example, a 150mm cast iron pipe on Wilking St. is selected that conforms to this classification description. Figure 5-12 shows all information in the ArcGIS interface. The engineer - assigned condition classifier is $\mathbb{C}_{C_1}$ = VERY GOOD, the target classifiers are $\bar{\mathbb{C}}_{C_1}$ = VERY GOOD and model predicted condition classifier is $\bar{\bar{\mathbb{C}}}_{C_1}$ = VERY GOOD. This pipe did not experience any break, and it was constructed in 1977 with more than 25 years of Remaining Service Life. The engineer-assigned performance classifier is performance classifier is $\mathbb{C}_{P_3}$ = MODERATE, target performance classifier is $\bar{\mathbb{C}}_{P_2}$ = GOOD the model predicted performance classifier for this pipe is $\bar{\bar{\mathbb{C}}}_{Cr_1}$ = GOOD. This pipe is not critical with a $\mathbb{C}_{Cr_1} = \bar{\mathbb{C}}_{Cr1} = \bar{\bar{\mathbb{C}}}_{Cr_1}$ = VERY LOW criticality classifier for engineer-assigned, target and model predicted. Thus, the mitigation result for all engineer-assigned, target and model predicted is $\mathbb{C}_{PAN_1} = \bar{\mathbb{C}}_{PAN_1} = \bar{\bar{\mathbb{C}}}_{PAN_1}$ = DO NOTHING. All pipes with DO NOTHING mitigation classes are prioritized at the bottom of the MWN list for any capital activity. The PAN for this Pipe is 220 that is low. Therefore, this pipe does not qualify for any capital work activity, as the model confirms.

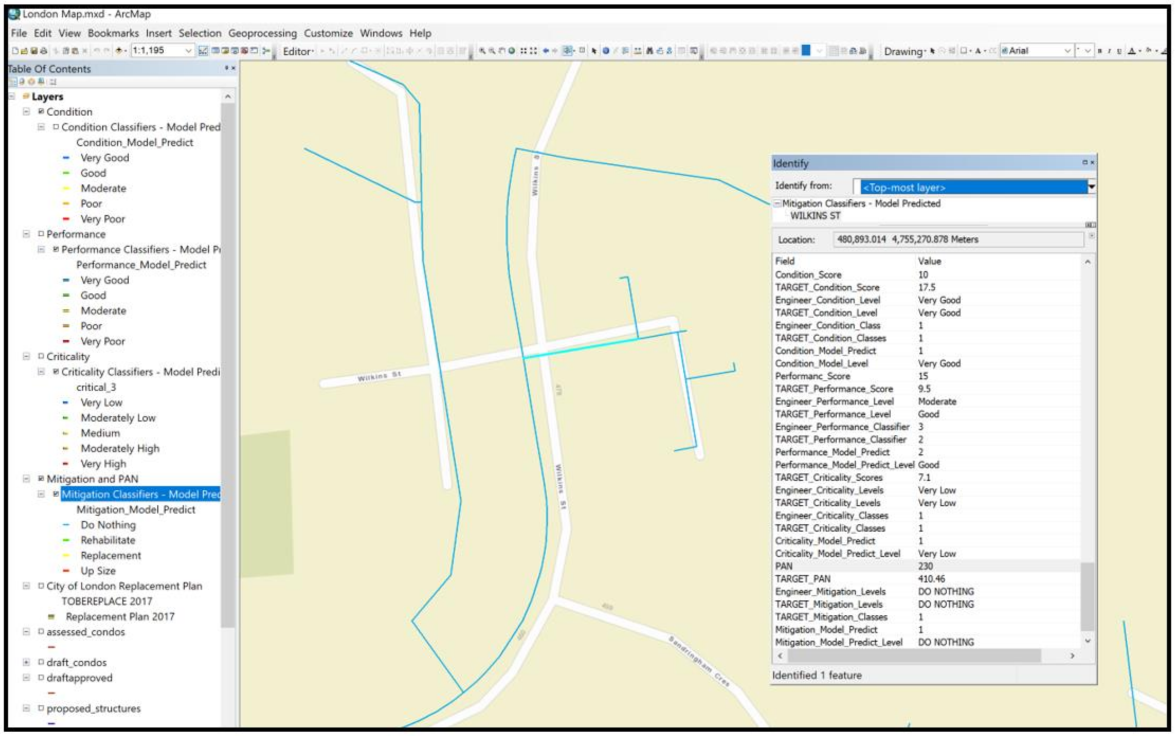

Figure 5-12 DO NOTHING Example

5.4.2 RELINE-REHAB Mitigation Classification

The second mitigation classifier is $\bar{\bar{\mathbb{C}}}_{PAN_2}$= RELINE – REHAB using trenchless technology. The algorithm identified 2435 pipes from the City of London in this category. These pipes only need minor maintenance work to extend their service life. Figure 5-13 shows the location of these pipes.

Figure 5-14 shows an example of a pipe identified for $\bar{\bar{\mathbb{C}}}_{PAN_2}$= RELINE- REHAB. The selected pipe is a 150mm cast iron pipe located on Nashua Ave. constructed in 1967. This pipe has -4 Remaining Service Life and only break once. This pipe identified as $\mathbb{C}_{C_5}$= POOR by engineers and experts $\bar{\mathbb{C}}_{C_5}$= POOR and the model $\bar{\bar{\mathbb{C}}}_{C_5}$= POOR for condition classifier. The engineer-assigned performance classifier is $\mathbb{C}_{C_3}$= MODERATE but expert's assigned $\bar{\mathbb{C}}_{C_2}$= GOOD performance classifier. The model result performance classifier is $\bar{\bar{\mathbb{C}}}_{P_2}$= GOOD.

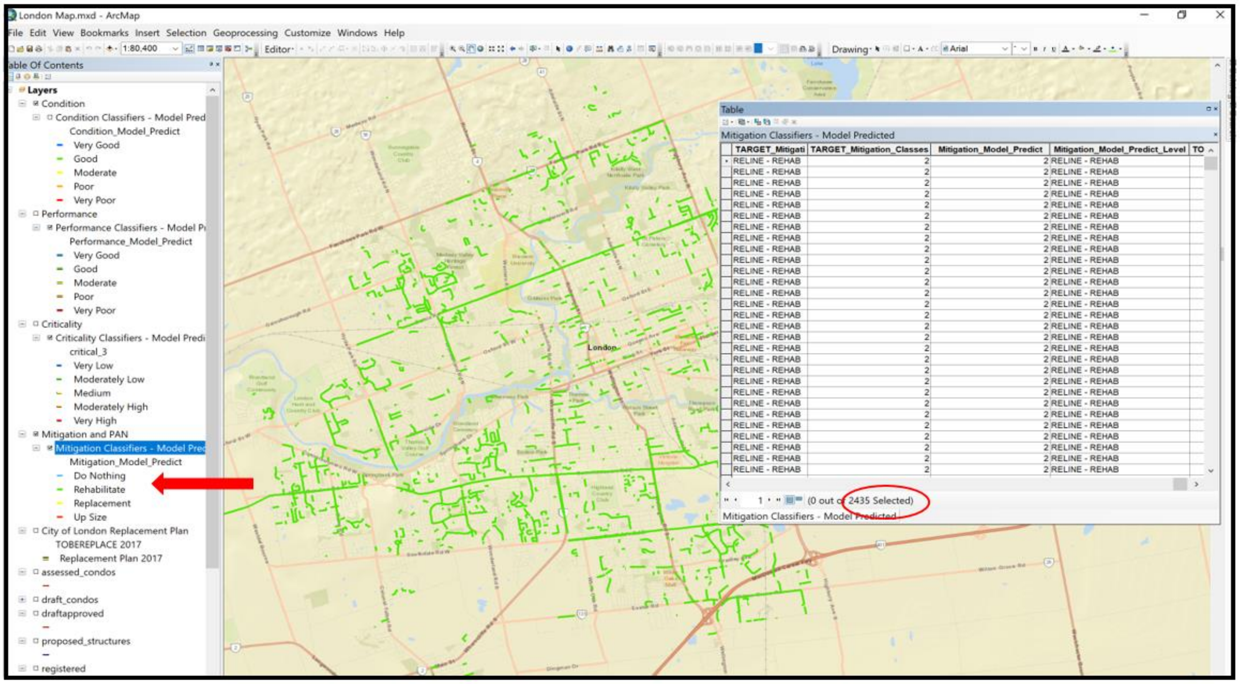

Figure 5-13 RELINE – REHAB Mitigation Results

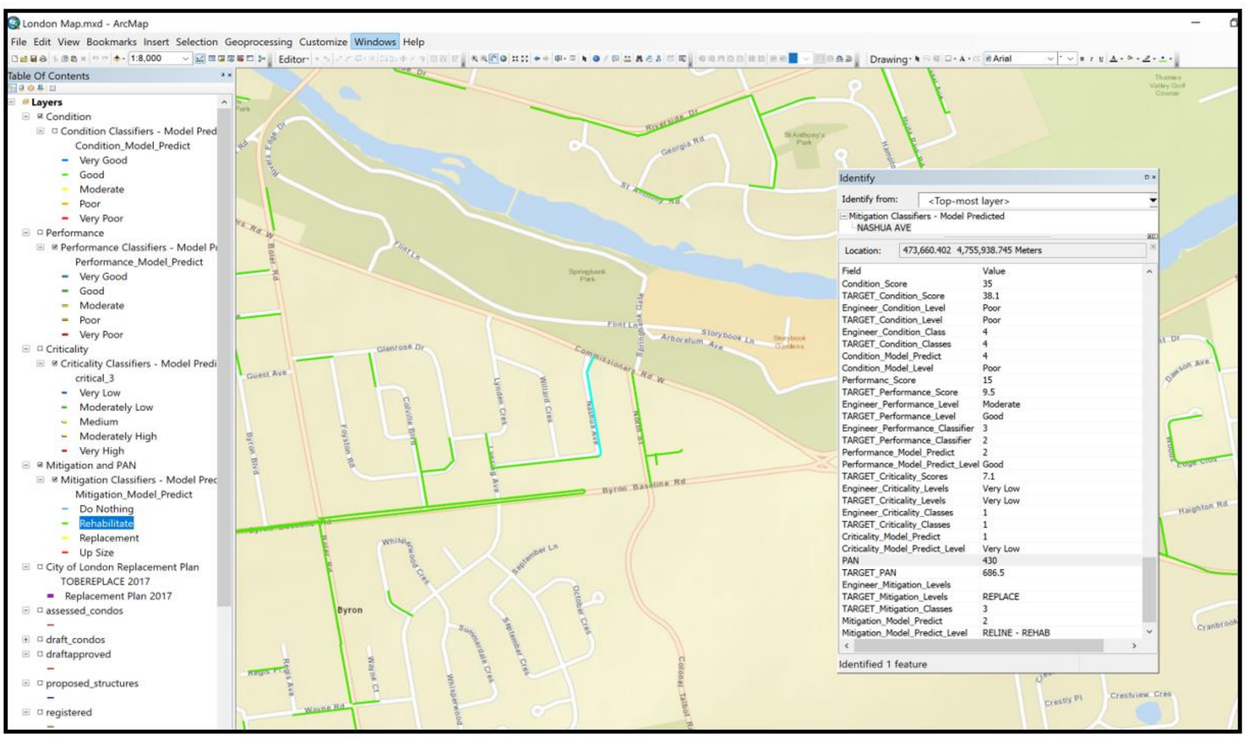

Figure 5-14 RELINE – REHAB Example

This pipe is identified $\mathbb{C}_{Cr_1}$= $\bar{\mathbb{C}}_{Cr_1}$= $\bar{\bar{\mathbb{C}}}_{Cr_1}$= VERY LOW criticality class by an engineer, experts and model. This pipe is identified for $\bar{\bar{\mathbb{C}}}_{PAN_2}$= RELINE-REHAB by the algorithm. The PAN for this Pipe is 430, and according to Figure 5-14 is in the RELINE-REHAB bin. The criticality of this Pipe is $\bar{\bar{\mathbb{C}}}_{Cr_1}$= VERY LOW; therefore, this pipe is not in urgent need of rehabilitation and will plan after pipes with $\bar{\bar{\mathbb{C}}}_{Cr_5}$= VERY HIGH, $\bar{\bar{\mathbb{C}}}_{Cr_4}$= MODERATELY HIGH, $\bar{\bar{\mathbb{C}}}_{Cr_3}$= MEDIUM and $\bar{\bar{\mathbb{C}}}_{Cr_2}$= MODERATELY LOW criticality classes.

5.4.3 REPLACE Mitigation Classification

The third classifier in the mitigation model is $\bar{\bar{\mathbb{C}}}_{PAN_3}$= REPLACE. Figure 5-15 shows locations of the pipes that are identified for replacement by the algorithm locations. There are 5512 pipes from the City of London water network classified in this category.

Figure 5-16 shows an example of a pipe that is identified for replacement by the model. It is a 150mm spun-cast iron located in Riverside Dr. This Pipe is constructed in 1961 and has ten years Remaining Service Life. This pipe experienced three breaks in the recent five years. This pipe is classified as $\mathbb{C}_{C_3}$= MODERATE condition by municipal engineer, $\bar{\mathbb{C}}_{C_4}$= POOR condition by expert and $\bar{\bar{\mathbb{C}}}_{C_4}$= POOR by the NBC supervised learning algorithm. This pipe has $\mathbb{C}_{P_3}$= MODERATE performance class by municipal engineer, $\bar{\mathbb{C}}_{P_2}$= $\bar{\bar{\mathbb{C}}}_{P_2}$= GOOD performance classifier by experts and the model. This pipe is identified as $\bar{\mathbb{C}}_{Cr_5}$= VERY HIGH criticality by experts, but engineer -assigned criticality and model result classifier is $\mathbb{C}_{Cr_4}$= $\bar{\bar{\mathbb{C}}}_{Cr_4}$= MODERATELY HIGH criticality. This pipe is classified for replacement by the model with 570 PAN. According to Table 5-10, this pipe is in the REPLACEMENT bin. This pipe would be prioritized before pipes with $\bar{\bar{\mathbb{C}}}_{Cr_3}$= MEDIUM, $\bar{\bar{\mathbb{C}}}_{Cr_2}$= MODERATELY LOW and $\bar{\bar{\mathbb{C}}}_{Cr_1}$= VERY LOW criticality classes and after pipes with $\bar{\bar{\mathbb{C}}}_{Cr_5}$= VERY HIGH criticality classifier.

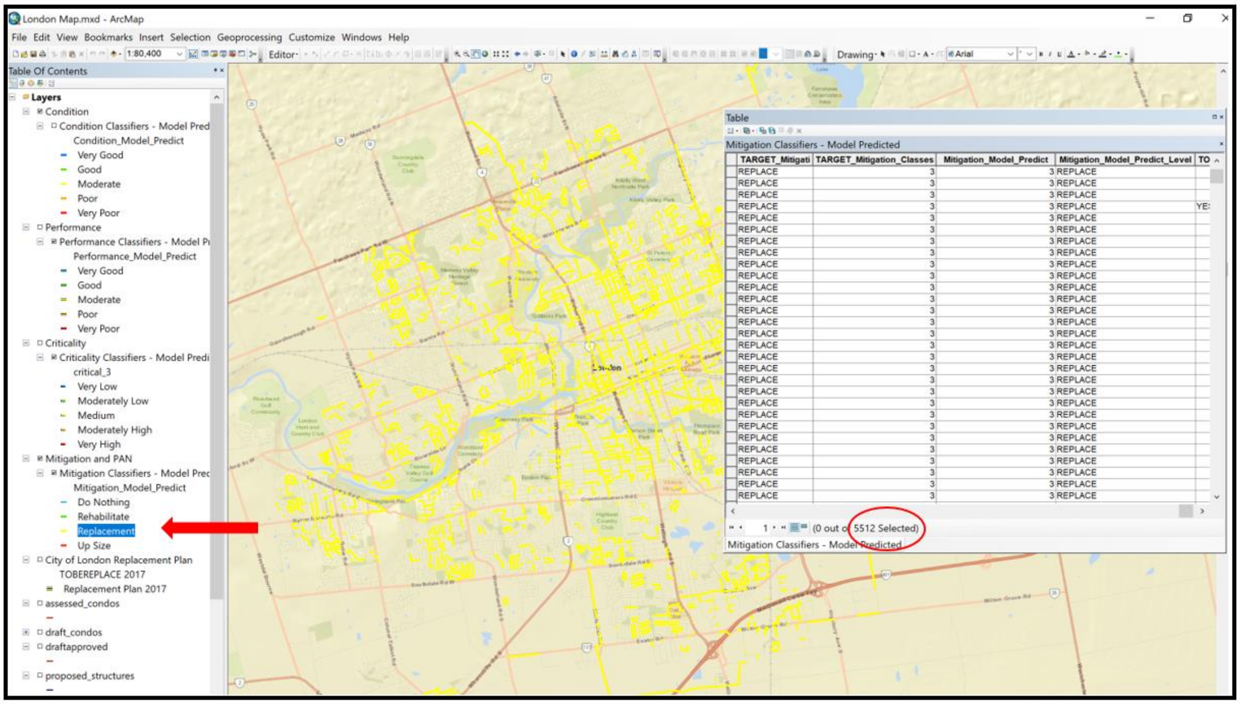

Figure 5-15 REPLACE Mitigation Results

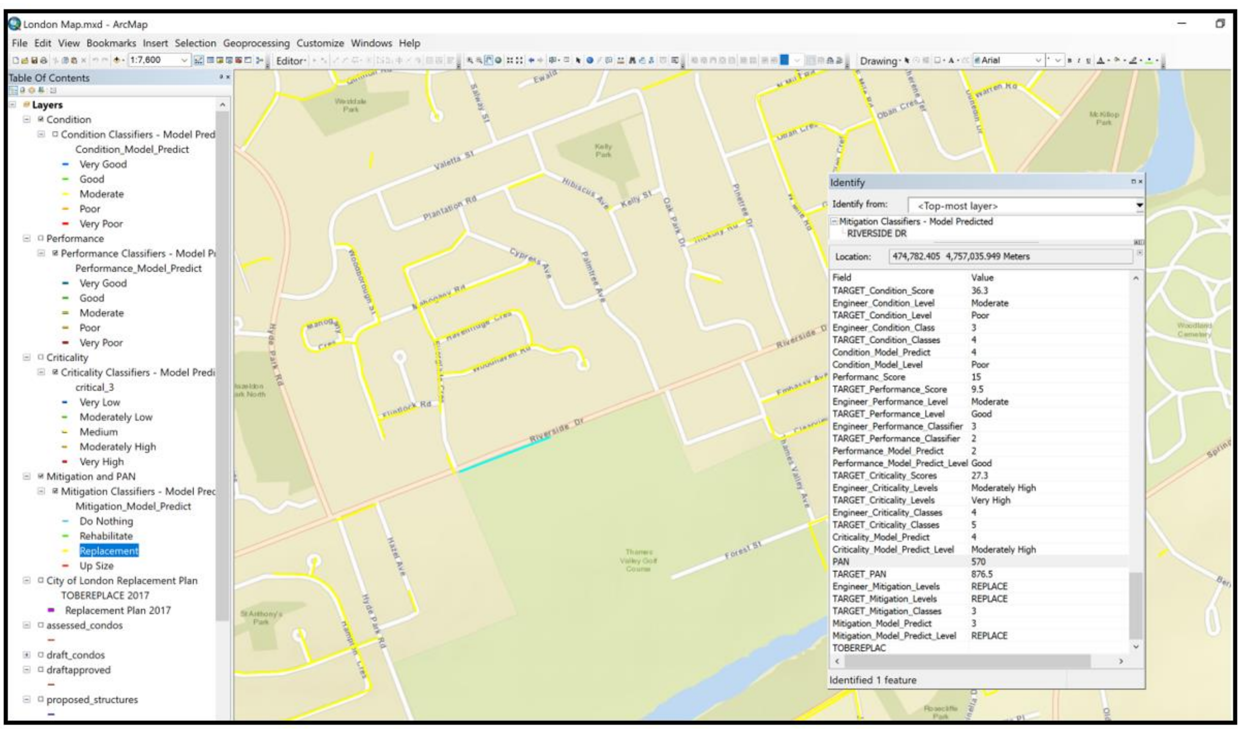

Figure 5-16 REPLACE Example

5.4.4 UP-SIZE Mitigation Classification

The last classifier in the mitigation model is $\bar{\bar{\mathbb{C}}}_{PAN_4}$= UP-SIZE. The model identified 150 pipes in the City of London MWN in this class. The location of these pipes is shown in Figure 5-17.

Figure 5-18 shows a $\bar{\bar{\mathbb{C}}}_{PAN_4}$= UP-SIZE mitigation class example. The selected example pipe is a 150mm cast iron pipe located on Tabbart Terr. This pipe is constructed in 1956 and has the Remaining Service Life of -11 (11 years passed from its designed life). This pipe experienced 17 breaks in its lifespan and four breaks in the recent five years. This pipe is classified as $\mathbb{C}_{C_5}$= $\bar{\mathbb{C}}_{C_5}$= $\bar{\bar{\mathbb{C}}}_{C_5}$= VERY POOR condition for engineer-assigned, target and model predicted classifiers. This pipe is classified as $\mathbb{C}_{P_5}$= $\bar{\mathbb{C}}_{P_5}$= $\bar{\bar{\mathbb{C}}}_{P_5}$= VERY POOR performance for engineer-assigned, target and model predicted classifiers. This pipe appears in a $\mathbb{C}_{Cr_2}$= $\bar{\mathbb{C}}_{Cr_2}$= $\bar{\bar{\mathbb{C}}}_{Cr_2}$= MODERATELY LOW criticality classifier for all engineer-assigned, target, and model predicted classes. The PAN is 790 and according to Table 5-10 is in the UP-SIZING range. According to this pipe's criticality classifier of $\bar{\bar{\mathbb{C}}}_{Cr_2}$= MODERATELY LOW, this pipe would be prioritized after pipes with $\bar{\bar{\mathbb{C}}}_{Cr_3}$= MEDIUM, $\bar{\bar{\mathbb{C}}}_{Cr_4}$= MODERATELY HIGH, and $\bar{\bar{\mathbb{C}}}_{Cr_5}$= VERY HIGH model predicted criticality classifiers. For instance, the pipe in section 5.4.3 would be planned before the pipe in section 5.4.4.

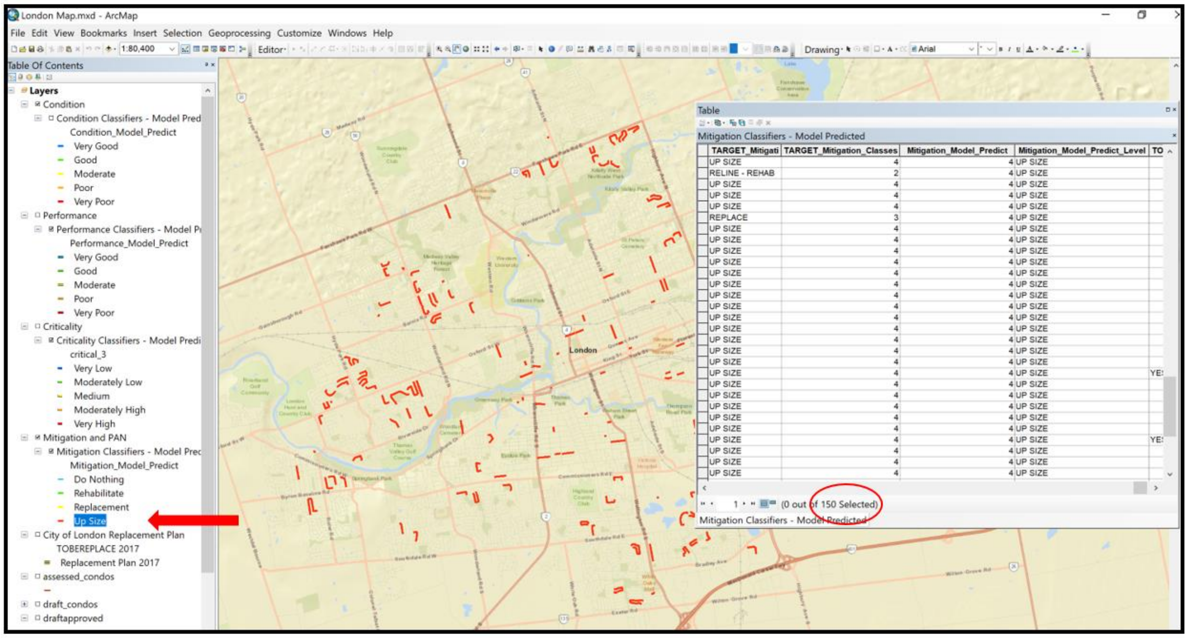

Figure 5-17 UP SIZE Mitigation Results

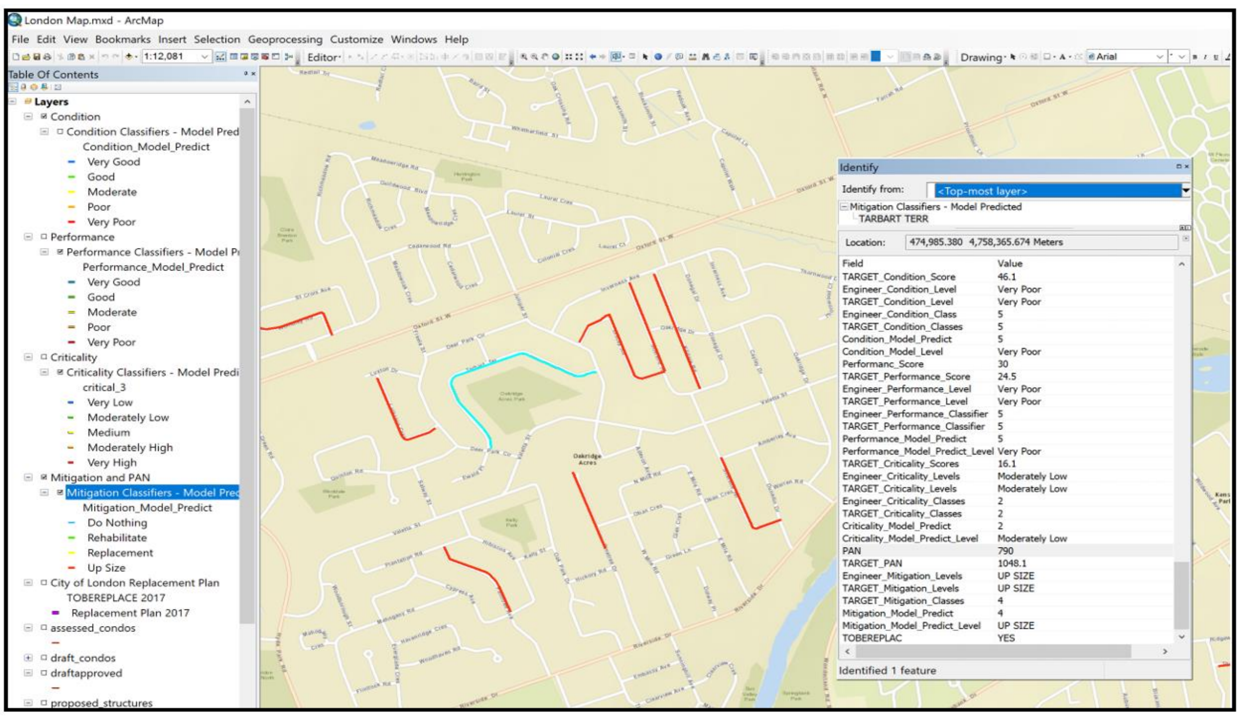

Figure 5-18 UP SIZE Example

5.4.5 Pipe Replacement Program Replication

In section two of this Chapter, the information received from the City of London, including the capital programs for watermain replacement planned for 2016 and 2017, is explained. This data is used to compare the City of London engineer assigned with the model results to validate model prediction and benchmark the proposed methodology for accuracy.

The City of London water pipe replacement program data is mapped in ArcGIS shown in Figure 5-19. The City of London planned watermain replacement for 109 pipes for a total length of 16 km in 2016 and 2017. The replacement methodology is the only technology used in the City of London. Table 5-11 summarizes the replacement program, and Table 5-12 shows the age of pipes selected to be replaced by the City of London engineers. The majority of the selected pipes are less than 300mm in diameter. Most of the selected pipes have more than 100 years of age that suggests condition attributes such as pipe vintage driving the replacement capital program decision by engineers in the City of London. As explained in Chapter 2, pipe age and Remaining Service Life are not the same. Therefore, for comparison between pipe age and the pipe's Remaining Service Life, Table 5-13 shows the Remaining Service Life of the selected pipes. The majority of the selected pipes have less than 15 years of Remaining Service Life, but there are 12 pipes with more than 50 years Remaining Service Life.

Figure 5-20 shows the comparison between the City of London replacement program and the mitigation model results. As expected, 85 pipes from the total of 109 selected pipes are also chosen for $\bar{\bar{\mathbb{C}}}_{PAN_3}$= REPLACEMENT by the model. Fourteen pipes are identified for $\bar{\bar{\mathbb{C}}}_{PAN_2}$= REHAB-RELINE by the model and could be REHAB-RELINE instead of REPLACEMENT, and ten pipes needed to be $\bar{\bar{\mathbb{C}}}_{PAN_4}$= UP-SIZED due to their performance issues that are not going to be resolve by replacement. This result would confirm the accuracy of the model for the capital plan. Figure 5-21, Figure 5-22 and Figure 5-23 show the model predicted condition, performance and criticality classifiers $\bar{\bar{\mathbb{C}}}_{C_j}$, $\bar{\bar{\mathbb{C}}}_{P_j}$and $\bar{\bar{\mathbb{C}}}_{Cr_j}$for the selected City of London pipes. The priority for replacing these pipes is dubious since the criticality model $\bar{\bar{\mathbb{C}}}_{Cr_j}$shows that not all these pipes are critical. The model result is calibrated by the expert opinion; the PAN for the selected pipes is compared with the total City of London database PAN to determine the priority ranking for the selected pipes by City of London Engineers. Figure 5-24 presents PAN for all City of London water pipes. There are 1008 pipes with PAN larger than 500 in the City of London database. Figure 5-25 presents the PAN for the selected 109 pipes. There are 44 pipes out of 109 selected pipes with PAN less than 500. It suggests the city of London has more critical pipes, according to experts, that require more immediate attention than the selected 109 pipes by the City of London Engineers.

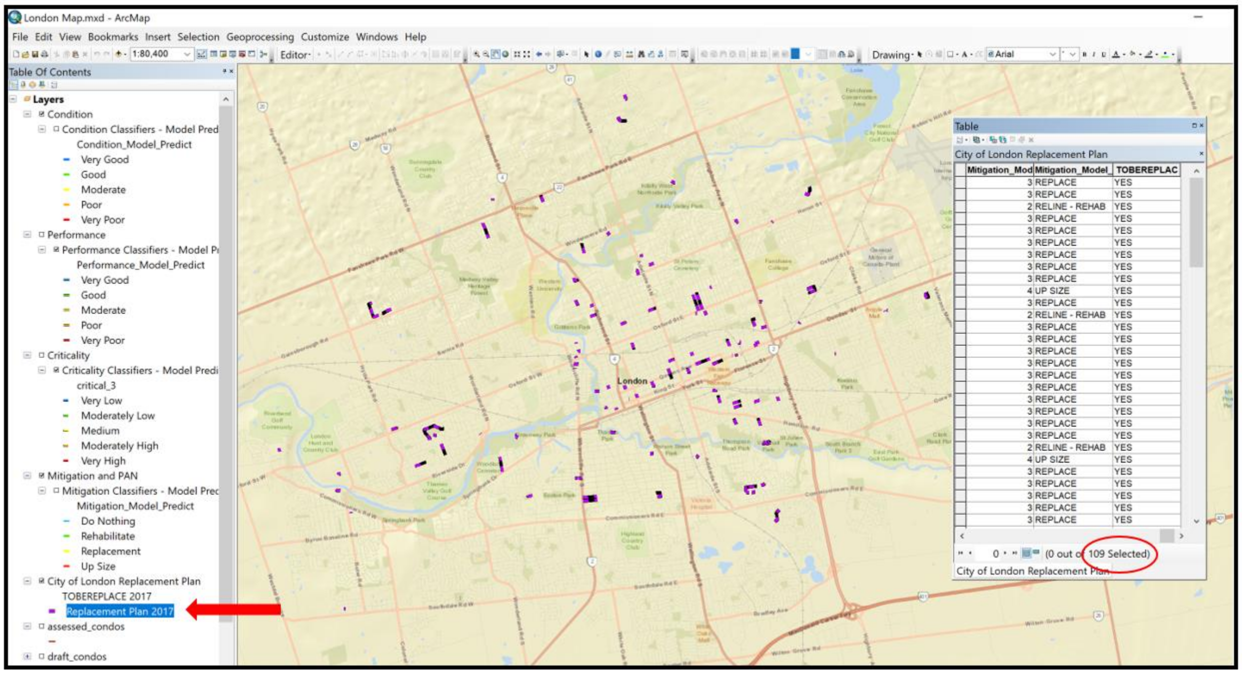

Figure 5-19 City of London Replacement Program

Table 5-11 City of London Pipe Replacement Program, Pipe Diameter and Pipe Length

Pipe Diameter (mm)	# of pipe	Pipe Length (m)
D < 300	108	16081.1
300 < D < 600	0	0.0
600 < D < 750	1	38.1
D >750	0	0.0

Table 5-12 City of London Replacement Program Pipe Age

Pipe Age (Years)	# of pipe	Pipe Length (m)
<50	17	2079
50-70	13	4098
70-80	0	0
80-90	6	1203
90-100	4	499
>100	69	8240

Table 5-13 City of London Replacement Program Remaining Service Life (RSL)

RSL (Years)	# of pipe	Pipe Length (m)
RSL≤ 15	96	14294.2
15 < RSL ≤ 30	0	0.0
30 < RSL ≤ 50	1	6.3
RSL >50	12	1818.7

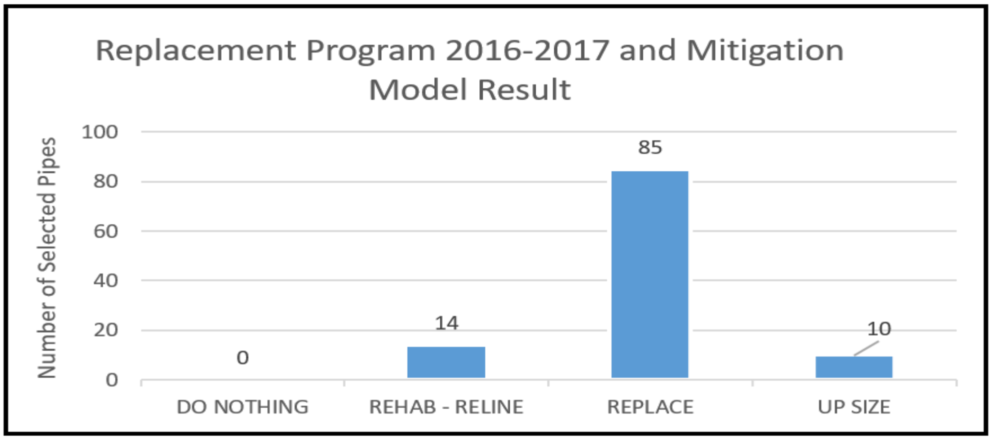

Figure 5-20 City of London Replacement Program vs Mitigation Model Result

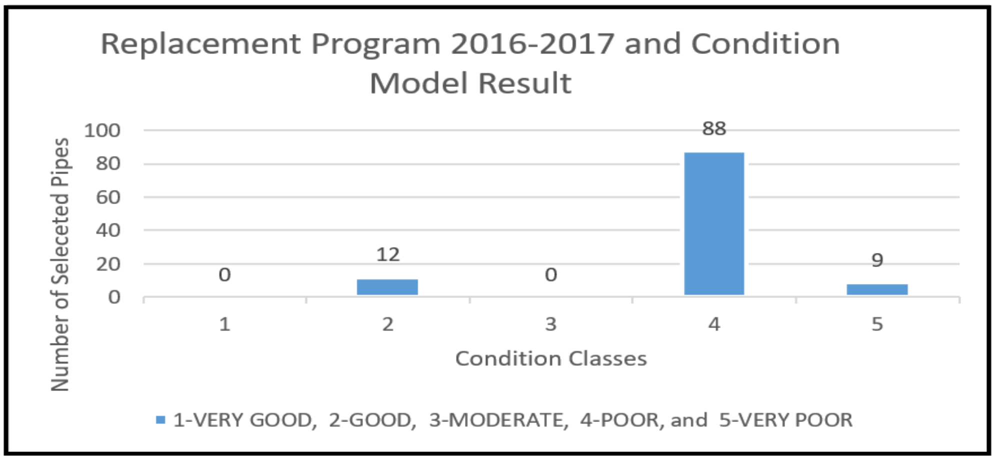

Figure 5-21 City of London Replacement Program vs Condition Model Result

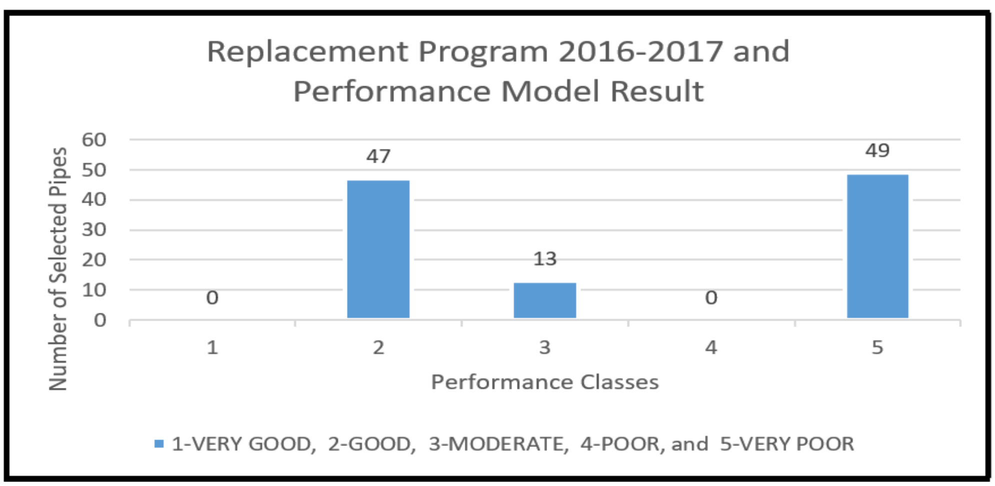

Figure 5-22 City of London Replacement Program vs Performance Model Result

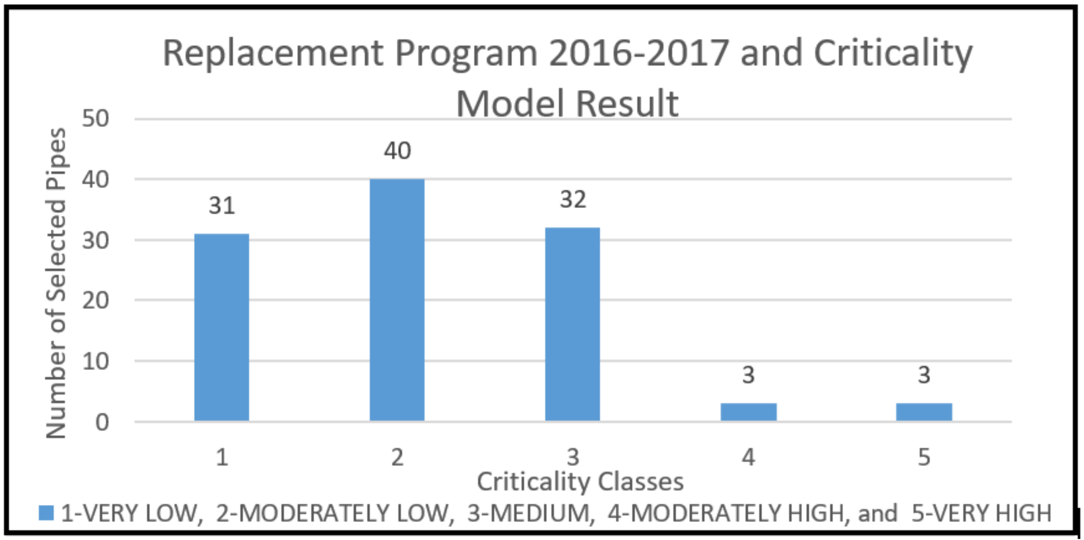

Figure 5-23 City of London Replacement Program vs Criticality Model Result

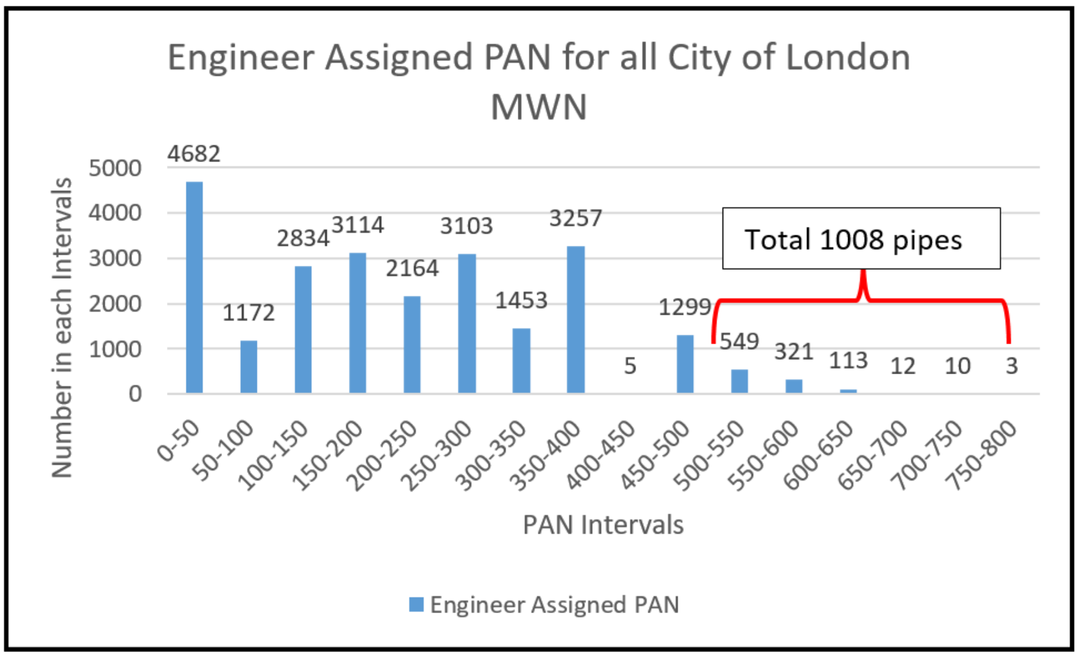

Figure 5-24 Municipal Engineer Assigned PAN for all City of London Water pipes

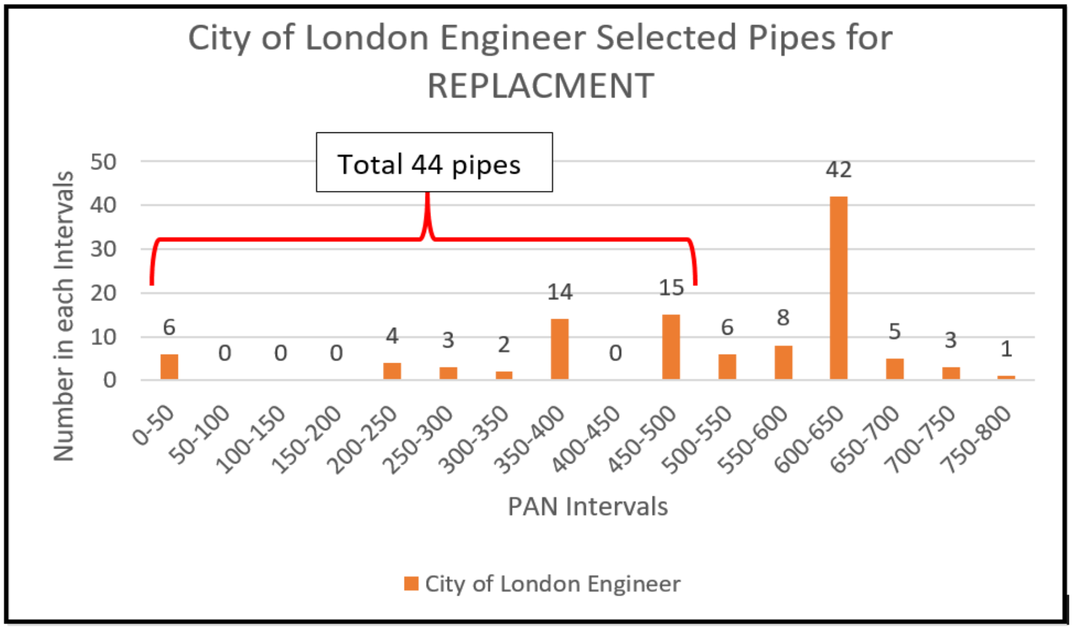

Figure 5-25 City of London Engineer Assigned PAN for 109 Pipes Selected for Replacement

5.5 Conclusions

Currently, capital program decisions are made manually by very few engineers in the City of London. Different professionals would have a different opinion, and water infrastructure suffers from bias decisions for a long time. In this study, a novel analysis on water pipes applied NBC supervised learning algorithm on the City of London comprehensive MWN database. This model is used to determine capital activities based on every pipe's condition, performance, and criticality in the City of London water network. This method is to benchmark and add defence-ability to capital asset planning and prioritize maintenance activities. Using a supervised machine learning algorithm would help municipalities to use their resources smarter. All models are built using real water pipe data from a municipality in southern Ontario. It is tested and validated with a large MWN database from the City of London.

Managing ageing water assets to keep their level of service through their life cycle can add up to billions of dollars for every city. Municipalities could use their resources in much-needed capital work such as repair, rehabilitation or replacement (Aven, 2016). There is a need to rank the entire water network to prioritize necessary capital activities of assets that needed the most attention ((NRC•CNRC), 2003). Using a machine learning approach to develop a prediction model that can replicate expert opinion (target values) for condition, performance and criticality, and a mitigation plan for the entire water system would be a very smart solution addressing the resource usage. This methodology would be a revolutionary standard for water linear asset management. This methodology would fill the neglected water infrastructure knowledge gap. These models' outputs can benchmark the capital work activities and add consistency and defence-ability to capital works planning.

These models significantly improve and automate watermain capital project decision-making process. The outputs of these models make proactive maintenance and keeping watermain service level at entire municipality possible.

Chapter 6

Conclusions, contributions, and future research

6.1 General conclusions

Specific conclusions for various aspects of this research are provided in Chapters 2 to 5 under their respective conclusion sections. A general summary is presented below.

The development of a novel approach to a valuable link between strategic, tactical, and operational levels to evaluate the watermain system is proposed. The proposed methodology automates the capital planning process using AI with NBC with a supervised machine learning algorithm that is able to replicate expert opinions. This study would be the first of its kind to investigate the feasibility of developing a multiple criteria scoring system and measure the weighting factors among different parameters to quantify the condition, performance, and criticality of the watermain section based on expert opinion. This methodology is using NBC supervised learning algorithm to measure the condition, performance and criticality and assign a capital activity to all pipes in the water network based on the expert's opinion for the first time. This methodology provides the prioritization measurements to assigned capital activities. Finally, this method could be applied as a decision-making support tool for a smarter, safer, more reliable watermain system that saves taxpayers money.

6.2 Statement of Contributions

This research makes the following original contribution to the state of knowledge:

1. A novel Priority Action Number is developed to prioritize the watermain capital planning activities.
2. A scientific methodology is developed to capture and organize expert's opinions about the different variables affecting the water pipe condition, performance, criticality and water capital activities.

3. A Naïve Bayes Classifier with a supervised machine learning algorithm is used to replicate the expert's opinion to classify all pipes in the MWN for condition, performance and criticality.
4. A Naïve Bayes Classifier with a supervised machine learning algorithm to replicate the expert's opinion for capital work activities and assign mitigation technology to all pipes in the MWN
5. Model application is presented on City of London water network ranking all water pipes for condition, performance and criticality and assigned a capital activity for each pipe calibrated with expert's opinion.
6. Model validation is presented by comparing the City of London water replacement program for 2016 and 2017 with the model results.

Figure 6-1 presents the specific contributions being made in each chapter of this thesis.

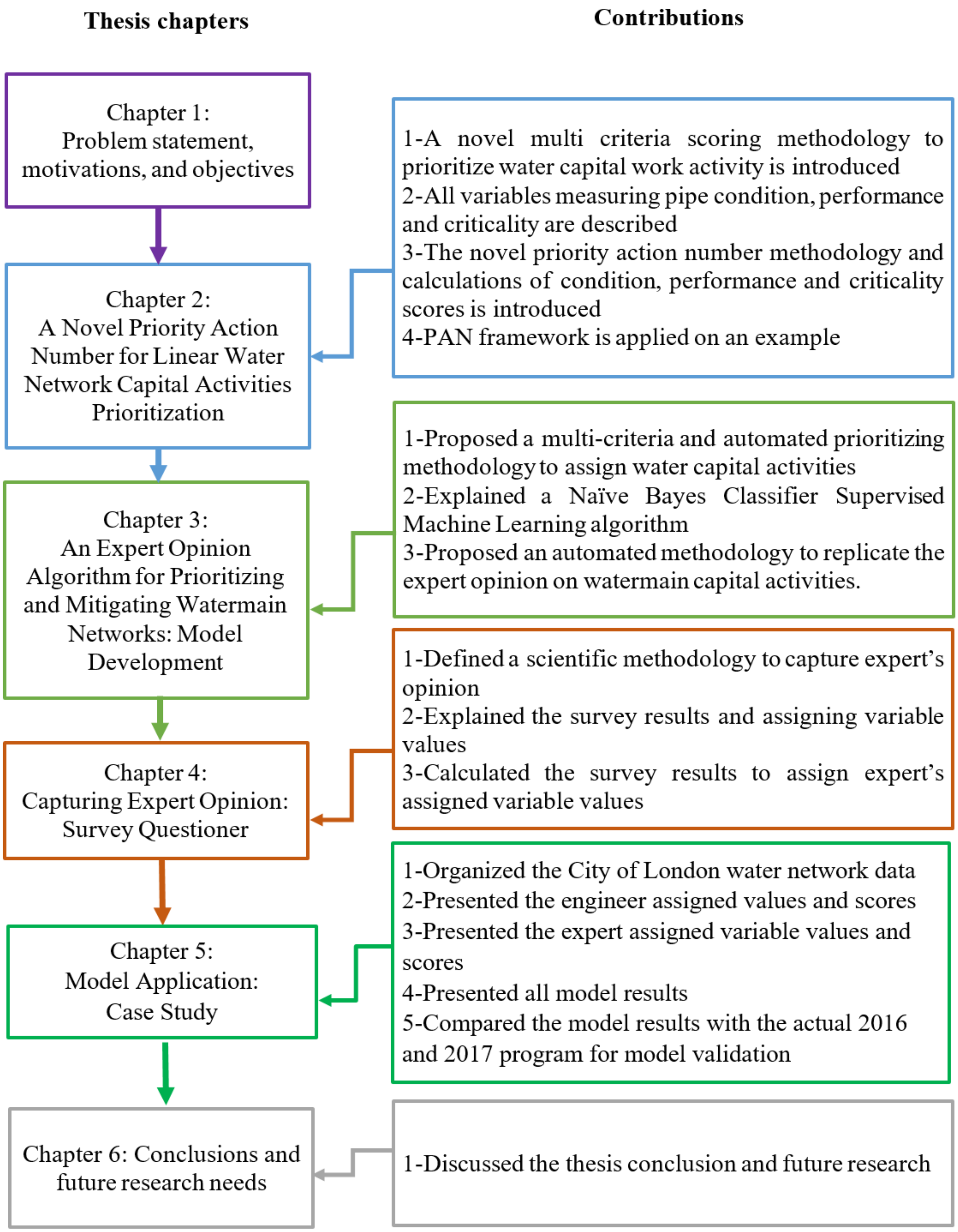

Figure 6-1: Contributions made in each chapter.

6.3 Future research

This research's most important contribution is that it presents an innovative framework for automating capital work planning and assessing the entire MWN in a faster and more efficient methodology. However, the application of this framework can be extended to each municipality based on their chosen attributes variables. Supported by the same conceptual framework, each municipality may further be extended by including the following ideas:

1. Extension of the expert's opinion to a broader geographical area, for example, expand the survey to international municipal engineers to calibrate the model with a more comprehensive expert opinion
2. More comprehensive survey questioner to cover additional pipe scenario's for more clarity about expert's opinion on assigning mitigation technology
3. Add more variables prioritization and mitigation models to coordinate with other capital projects at the same location, such as sanitary sewer, storm sewer and road work
4. Improving the model with continuous update time, such as adding an additional dimension to the database to predict the classifiers for future years
5. Improving the variables meaningfulness, such as add hydrological model to condition classifier to have more accurate pressure loss and head loss variable values
6. Coordinating with other models such as Ganjidoost (2020) for capital program enhancement to group the assigned capital projects into a capital program to realize the cost-saving benefits

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Appendices

Appendix A

Survey Questioner and Survey Results

A 1 Appendix A1 - Survey Questioner

A 1.1 Survey Part I - Background Information about the Expert Respondents

Prioritizing Water Capital Work Projects

1.

20%

The objective of this anonymous survey is to provide a ranking system for prioritizing watermain capital work based on expert opinion. Your response will help to build an automated system based on expert opinion.This proposed system is to benchmark decision making process for all water asset planning.
This survey data will be used for a PHD research on watermain replacement and rehabilitation.
The information will potentially be useful for a variety of stakeholders – city engineers/managers, contractors, consultants, manufacturers and political decision makers.

Next

Prioritizing Water Capital Work Projects

2. Background Information

40%

* **1. What province or territory are you located in?**

* **2. What is the population of your municipality?**

- < 30,000 (Small Municipality)
- 30,000 - 100,000 (Medium Municipality)
- > 100,000 (Large Municipality)

Prev   Next

Prioritizing Water Capital Work Projects

3. Asset Management and Network Financial Information

60%

3. Is asset management a separate group in your municipality or is it part of water/wastewater operations?

- ◯ Separate Group
- ◯ Water/wastewater Operations

Other (please specify)

4. What is the asset management (AM) maturity level? (Advanced means that you know the current condition of your system well, have defined level of service, developed condition assessment and operation, maintenance, and renewal plans, and have access to funds to implement and monitor the AM plan).

- ◯ No asset management
- ◯ Basic asset management
- ◯ Advanced asset management

if you choose "no asset management", please explain why?

5. During the current fiscal year, what is your municipality's estimated budget for capital works for rehabilitation and/or replacement of the following networks?

	< $500,000	$500,000 to $1 million	$1 million to $2 million	$2 million to $5 million	$5 million to $10 million	> $10 million
Water Distribution Network	◯	◯	◯	◯	◯	◯
Wastewater Network	◯	◯	◯	◯	◯	◯
Stormwater Network	◯	◯	◯	◯	◯	◯

6. Does your municipality/utility have sufficient funds to meet operation and maintenance (O&M) expenditures?

◯ We do not have sufficient funds to meet O&M requirements

◯ We have just enough funds to meet O&M requirements

◯ We have sufficient funds to meet O&M requirements

Other comments (please specify)

7. Does your municipality/utility have sufficient funds to meet capital expenditures for the next 5-10 years?

◯ We do not have sufficient funds

◯ We have just enough funds

◯ We have sufficient funds

Other comments (please specify)

8. What is the estimated total length of watermains in your municipality?

	< 300km	300-499km	500-800km	> 800km
Total Length	○	○	○	○

9. What is the average age of watermains in your municipality?

	<30 Years	30-49 Years	50-70 Years	>70 Years
Average age of pipes	○	○	○	○

10. What percentage of the following pipe diameters makes up the total watermains' network in your municipality?

	0 - 10%	11 - 20%	21 - 30%	31 - 40%	41 - 50%	50 - 60%	61 - 70%	71 - 80%	81 - 90%	91 - 100%
< 150mm	○	○	○	○	○	○	○	○	○	○
150mm	○	○	○	○	○	○	○	○	○	○
150-300mm	○	○	○	○	○	○	○	○	○	○
300 - 599mm	○	○	○	○	○	○	○	○	○	○
600 - 900mm	○	○	○	○	○	○	○	○	○	○
> 900mm	○	○	○	○	○	○	○	○	○	○

Prev Next

A 1.2 Survey Part II – Ranking Questions For Prioritization Models Target Variable Values

Prioritizing Water Capital Work Projects

4. Rating Questions

80%

11. How important are the groups below for watermain capital works (such as replacement or rehabilitation) decision making? Score of 1 to 5 (“1” is not important while “5” is extremely important).

	1 (Not Important)	2	3	4	5 (Extremely Important)
Remaining service life; Total number of watermain breaks; Number of breaks within recent 5 years; (Maintenance Index that is Pipe replacement cost divided by operation and maintenance cost over service life of the pipe).	○	○	○	○	○
Pipe diameter, Pipe located in environmentally sensitive area (e.g. crossing creek, providing service to hospital or long care facility), Pipe accessibility (e.g. under right of way or have proper size access easements, depth)	○	○	○	○	○

Low hydraulic capacity (e.g. flow issue, pressure issue, and adequate to service new development), Poor water quality (e.g. resident complains), Conformance to standard (standard change in material, diameter…)	○	○	○	○	○

Other (please specify)

12. How important is remaining service life of the watermain for capital works (such as replacement or rehabilitation) decision making? Score of 1 to 5 ("1" is not important while "5" is extremely important).

	1(Not Important)	2	3	4	5 (Extremely Important)
a) If estimated remaining service life of pipe is less than 15 years	○	○	○	○	○
b) If estimated remaining service life of pipe is between 15 and 29 years	○	○	○	○	○
c) If estimated remaining service life of pipe is between 30 and 50 years	○	○	○	○	○

Other (please specify)

13. How important is the total number of watermain breaks for watermain capital works (replacement or rehabilitation) decision making? Score of 1 to 5 (“1” is not important while “5” is extremely important).

	1 (Not Important)	2	3	4	5 (Extremely Important)
a) If total number of watermain breaks are more than 9 since the pipe was installed.	○	○	○	○	○
b) If total number of Watermain breaks are between 5 and 9 times since the pipe was installed.	○	○	○	○	○
c) If total number of Watermain breaks are between 1 and 4 times since the pipe was installed.	○	○	○	○	○
d) Watermain never experienced any breaks/ no watermain breaks since the pipe was installed.	○	○	○	○	○

14. Based on your experience, what is the estimated service life for the following pipe materials in non-corrosive soil conditions? (your answers should be in *Years)*

Asbestos Cement	
Cast Iron	
Ductile Iron	
PVC	
HDPE	
Pre-Stressed Concrete Cylinder Pipe	

15. Based on your experience, what is the estimated service life for the following pipe materials in corrosive soil conditions?(your answers should be in *Years*)

Asbestos Cement	
Cast Iron	
Ductile Iron	
PVC	
HDPE	
Pre-Stressed Concrete Cylinder Pipe	

16. Rank the following watermain quality scenarios with respect to watermain capital works (replacement or rehabilitation) decision making. Score of 1 to 5 ("1" is not important while "5" is extremely important).

	1(Not Important)	2	3	4	5 (Extremely Important)
a) Watermain with poor chlorine residual tests	○	○	○	○	○
b) Watermain with water quality related complaints	○	○	○	○	○
c) Unlined CI watermain	○	○	○	○	○
d) Watermain that was not installed according to current standards (for example: safe drinking water, engineering and construction design standard)	○	○	○	○	○

17. Rank the importance of the following pipe sizes with respect to watermain capital works (replacement or rehabilitation) decision making. Score of 1 to 5 ("1" is not important while "5" is extremely important).

	1 (Not Important)	2	3	4	5 (Extremely Important)
>900mm	○	○	○	○	○
750mm to 900mm	○	○	○	○	○
600mm to 750mm	○	○	○	○	○
400mm to 600mm	○	○	○	○	○
200mm to 400mm	○	○	○	○	○
150mm	○	○	○	○	○
<150mm	○	○	○	○	○

18. Rank the importance of the following pipe locations for watermain capital works (replacement or rehabilitation) prioritization. Score of 1 to 5 ("1" is not important while "5" is extremely important).

	1(Not Important)	2	3	4	5 (Extremely Important)
Watermain crossing watercourses such as creeks, rivers, and ponds	○	○	○	○	○
Watermain servicing hospitals, airports, and long term care centers	○	○	○	○	○
Watermain crossing power line corridors and high voltage poles	○	○	○	○	○
Watermain crossing gas and oil pipelines	○	○	○	○	○
Watermain crossing major intersections, highway crossings, and railway crossings	○	○	○	○	○
Watermain installed along narrow roads or with no easements	○	○	○	○	○
Watermain installed extra deep (for example: deeper than 5m) below ground surface	○	○	○	○	○
Watermain installed in areas without vehicle access	○	○	○	○	○

19. List any other possible factors that cause pipe location to be an important issue for watermain capital works (replacement or rehabilitation) decision making.

A 1.3 Survey Part III – Mitigation Questions – Based on Pipe Scenarios

20. For Pipe Group a) and b), select one of the following options: 1) do nothing, 2) open cut and replace with the same pipe size, or 3) renovate using trench-less technologies If:

	Do Nothing	Open cut and replace with the same pipe size	Renovate using trenchless technologies
a) 1- Pipe is **NOT** located in an environmentally sensitive area. 2- Pipe is in good condition. 3- Pipe meets current standards. 4- Pipe has **NO** flow capacity or water quality issues.	○	○	○
b) 1- Pipe is located in an environmentally sensitive area. 2- Pipe is in good condition. 3- Pipe meets current standards. 4- Pipe has **NO** flow capacity or water quality issues.	○	○	○

21. For Pipe Group a) and b), select one of the following options: 1) do nothing, 2) open cut and replace with the same pipe size, or 3) renovate using trench-less technologies If:

	Do Nothing	Open cut and replace with the same pipe size	Renovate using trenchless technologies
a) 1- Pipe is located in an environmentally sensitive area. 2- Pipe is **NOT** in good condition (high number of breaks in past 5 years). 3- Pipe meets current standards. 4- Pipe has **NO** flow capacity or water quality issues.	○	○	○
b) 1- Pipe is located in an environmentally sensitive area. 2- Pipe is **NOT** in good condition (high number of breaks in the past 5 years). 3- Pipe does **NOT** meet current standards. 4- Pipe has **NO** flow capacity or water quality issues.	○	○	○

22. For Pipe Group a) to d), select one of the following options: 1) do nothing, 2) open cut and replace with the same pipe size, or 3) renovate using trench-less technologies, If:

	Do Nothing	Open cut and replace with the same pipe size	Renovate using trenchless technologies
a) 1- Pipe is **NOT** located in an environmentally sensitive area. 2- Pipe is **NOT** in good condition (high number of breaks in the past five years). 3- Pipe does **NOT** meet current standards. 4- Pipe has **NO** flow capacity or water quality issues.	○	○	○
b) 1- Pipe is **NOT** located in an environmentally sensitive area. 2- Pipe is **NOT** in good condition (high number of breaks in the past five years). 3- Pipe meets current standards. 4- Pipe has **NO** flow capacity or water quality issues.	○	○	○

c)

1- Pipe is **NOT** located in an environmentally sensitive area.

2- Pipe is in good condition.

3- Pipe does **NOT** meet current standards.

4- Pipe has **NO** flow capacity or water quality issues.

d)

1- Pipe is located in an environmentally sensitive area.

2- Pipe is in good condition.

3- Pipe does **NOT** meet current standards.

4- Pipe has **NO** flow capacity or water quality issues.

23. What would be the appropriate capital works mitigation plan: 1) "open cut and replace with a larger pipe size", or 2) "open cut and replace with the same pipe size" If:

	Open cut and replace with a larger pipe size	Open cut and replace with the same pipe size
a) 1- Pipe is **NOT** located in an environmentally sensitive area. 2- Pipe is in good condition. 3- Pipe meets current standards. 4- Pipe **has** flow capacity or water quality issue.	○	○
b) 1- Pipe is **NOT** located in an environmentally sensitive area. 2- Pipe is in good condition. 2- Pipe does **NOT** meet current standards. 3- Pipe **has** flow capacity or water quality issue.	○	○
c) 1- Pipe is **NOT** located in an environmentally sensitive area. 2- Pipe is **NOT** in good condition (high number of breaks in the past 5 years). 3- Pipe meets current standards. 4- Pipe **has** flow capacity or water quality issue.	○	○

d)

1- Pipe is **NOT** located in an environmentally sensitive area.

2- Pipe is **NOT** in good condition (high number of breaks in the past 5 years).

3- Pipe does **NOT** meet current standards.

4- Pipe **has** flow capacity or water quality issue.

e)

1- Pipe is located in an environmentally sensitive area.

2- Pipe is **NOT** in good condition (high number of breaks in the past 5 years).

3- Pipe does **NOT** meet current standards.

4- Pipe **has** capacity or water quality issue.

f)

1- Pipe is located in an environmentally sensitive area.

2- Pipe is in good condition.

3- Pipe does **NOT** meet current standards.

4- Pipe **has** capacity or water quality issue.

g)

1- Pipe is located in an environmentally sensitive area.

2- Pipe is in good condition.

3- Pipe meets current standards.

4- Pipe **has** capacity or water quality issue.

h)

1- Pipe is located in an environmentally sensitive area.

2- Pipe is **NOT** in good condition (high number of breaks in the past 5 years).

3- Pipe meets current standards.

4- Pipe **has** capacity or water quality issue.

Prev Next

Prioritizing Water Capital Work Projects

5. Thank you for taking the time to fill this survey.

100%

24. Please fill out the information and your name will be entered into the draw for smartphones and/or tablets.

Name:

Company:

Address 1:

Address 2:

City/Town:

State/Province:

ZIP/Postal Code:

Country:

Email Address:

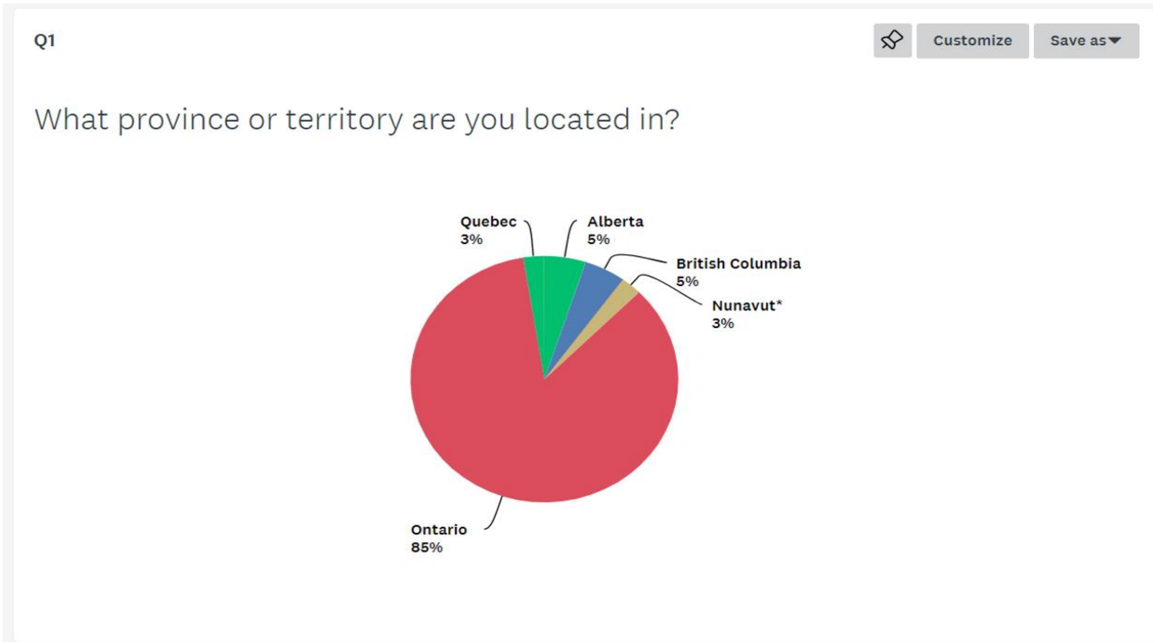
Phone Number:

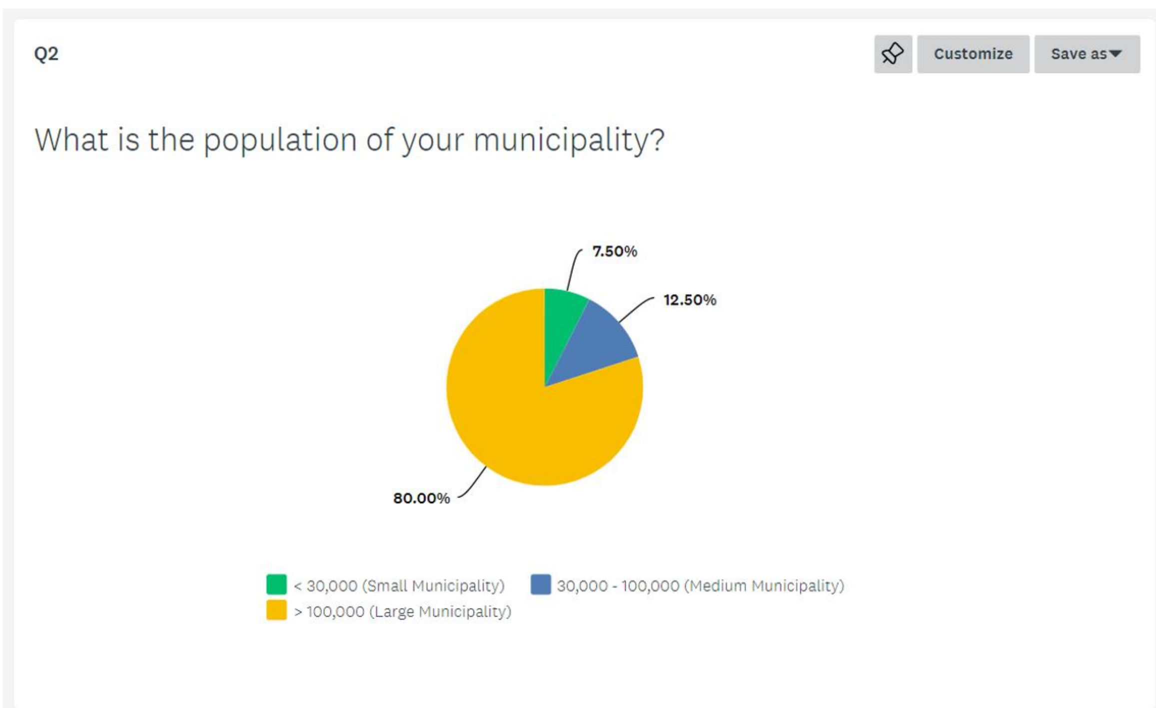
Prev Done

A 2 Appendix A2 - Survey Results and Details

A 2.1 Results Part I - Background Information about the Expert Respondents

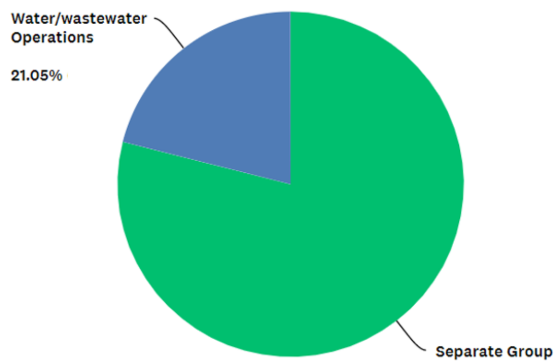
The first part of the survey gathered information about experts who filled this survey





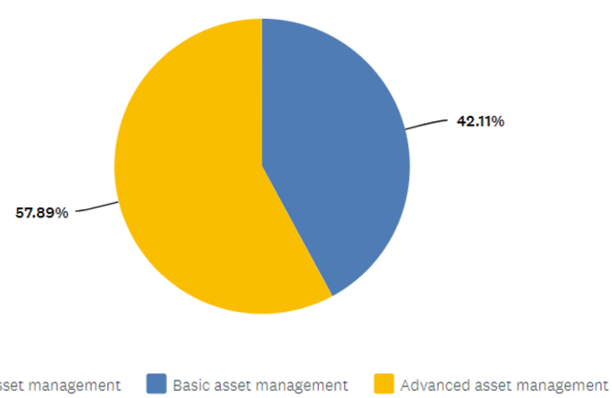
Q3 Customize Save as

Is asset management a separate group in your municipality or is it part of water/wastewater operations?



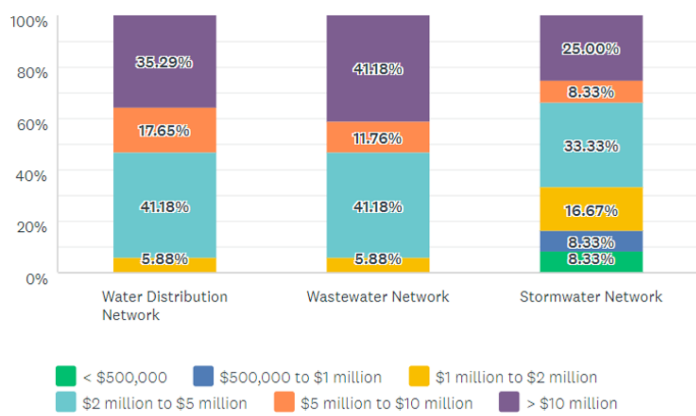
Q4 Customize Save as

What is the asset management (AM) maturity level? (Advanced means that you know the current condition of your system well, have defined level of service, developed condition assessment and operation, maintenance, and renewal plans, and have access to funds to implement and monitor the AM plan).



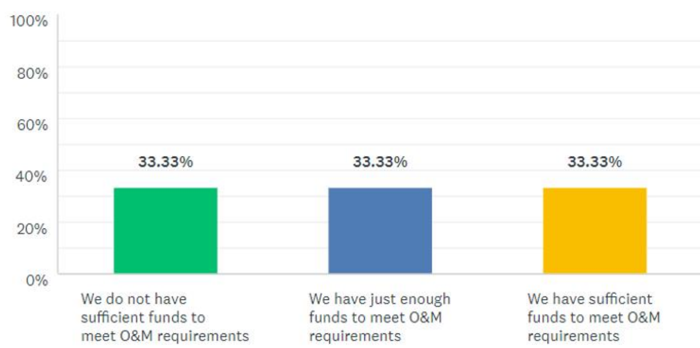
Q5

During the current fiscal year, what is your municipality's estimated budget for capital works for rehabilitation and/or replacement of the following networks?



Q6

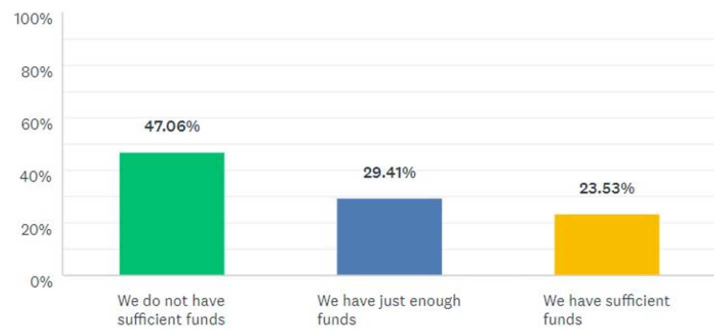
Does your municipality/utility have sufficient funds to meet operation and maintenance (O&M) expenditures?



Q7

Customize Save as

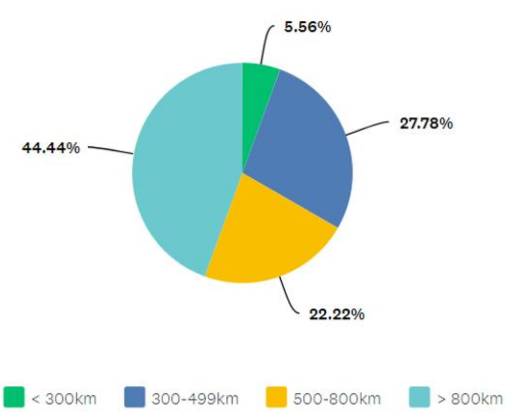
Does your municipality/utility have sufficient funds to meet capital expenditures for the next 5-10 years?



Q8

Customize Save as

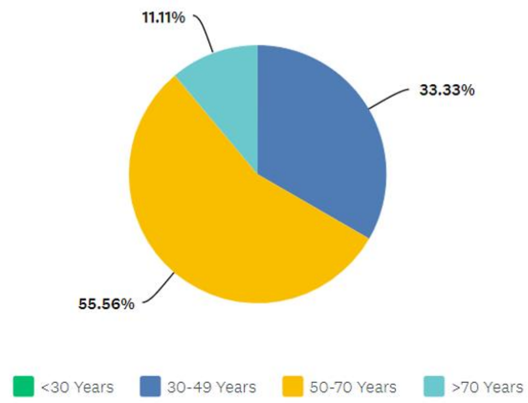
What is the estimated total length of watermains in your municipality?



Q9

Customize Save as

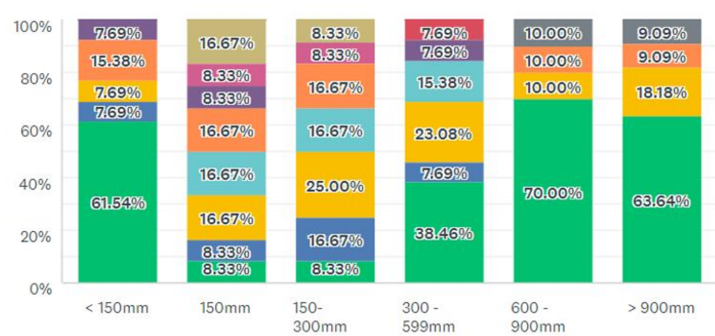
What is the average age of watermains in your municipality?



Q10

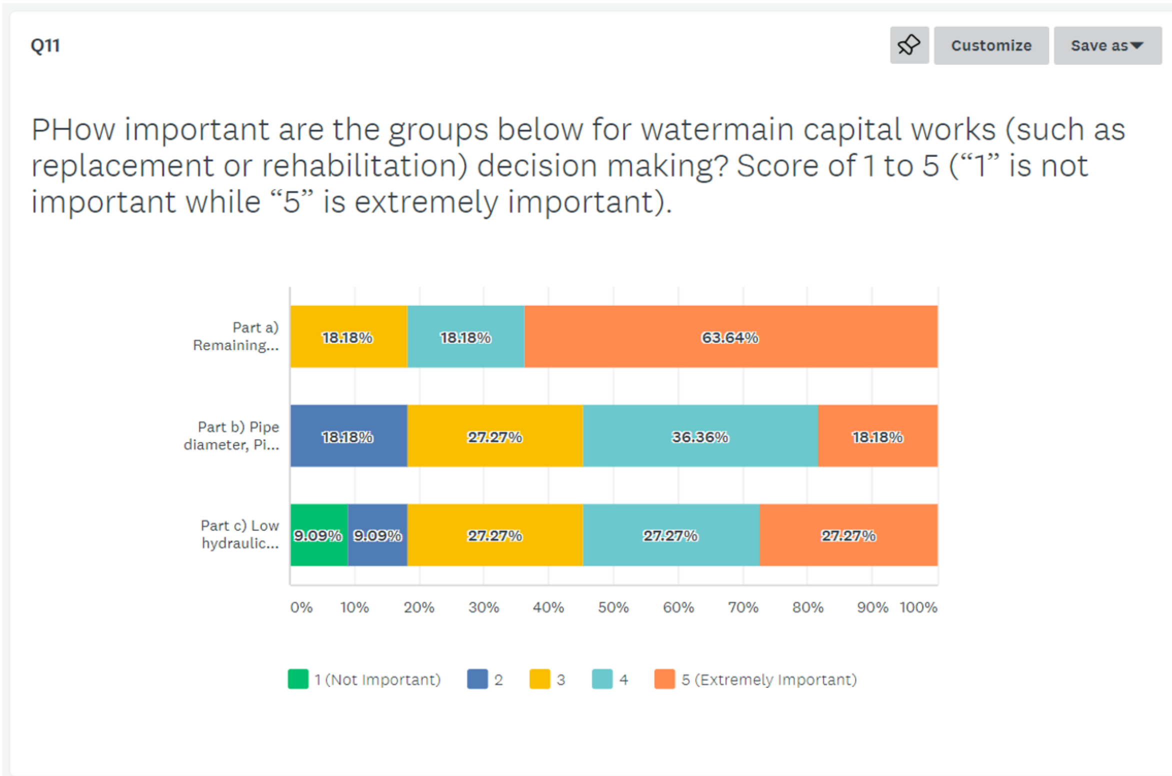
Customize Save as

What percentage of the following pipe diameters makes up the total watermains' network in your municipality?



A 2.2 Results Part II – Ranking Questions For Prioritization Models Target Variable Values

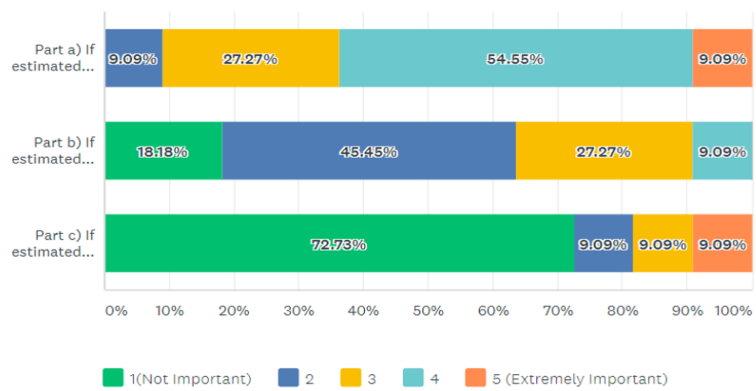
This section is designed to capture expert assigned variable values.



Q12

Customize Save as

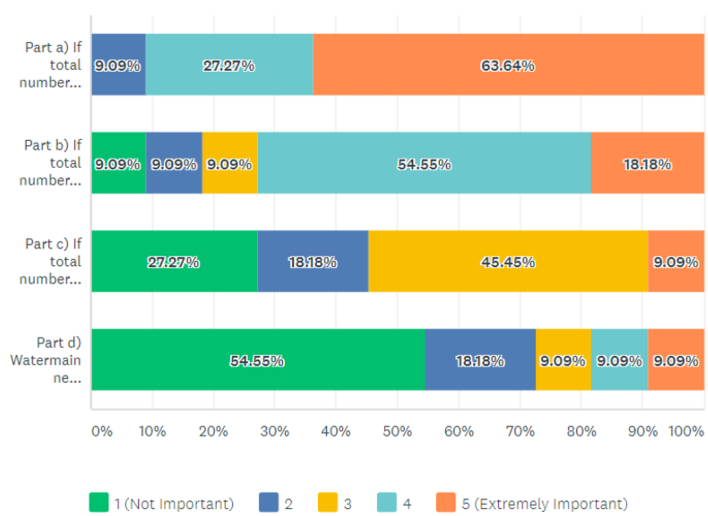
How important is remaining service life of the watermain for capital works (such as replacement or rehabilitation) decision making? Score of 1 to 5 (“1” is not important while “5” is extremely important).



Q13

Customize Save as

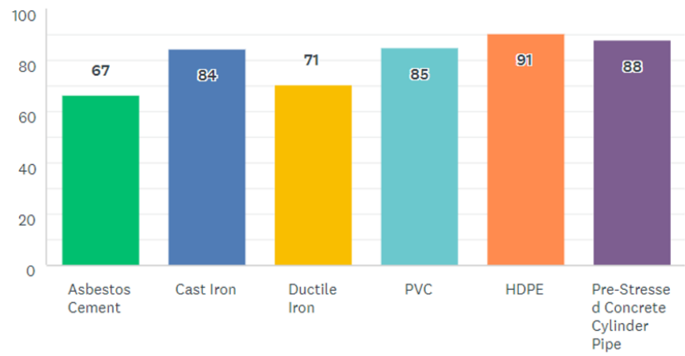
How important is the total number of watermain breaks for watermain capital works (replacement or rehabilitation) decision making? Score of 1 to 5 (“1” is not important while “5” is extremely important).



Q14

Customize Save as

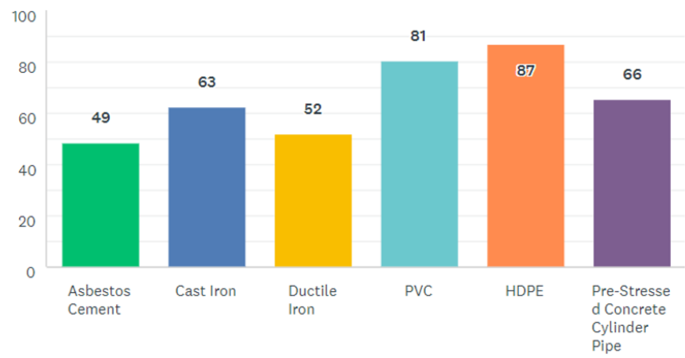
Based on your experience, what is the estimated service life for the following pipe materials in non-corrosive soil conditions? (your answers should be in Years)

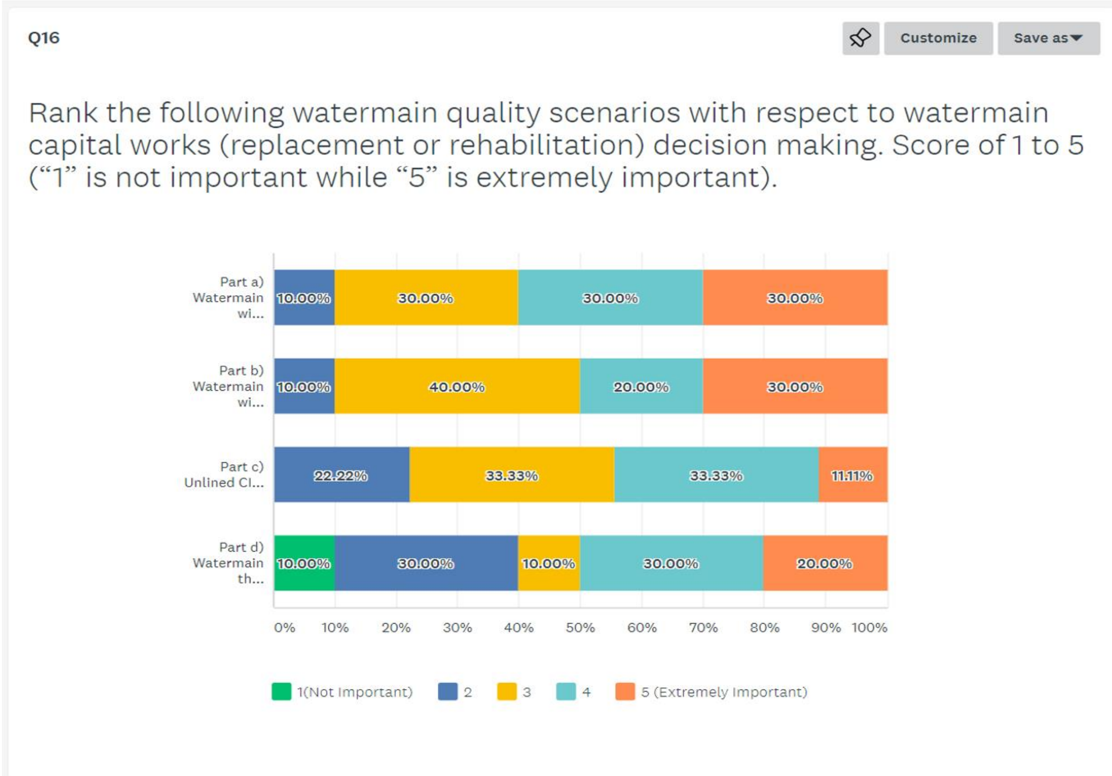


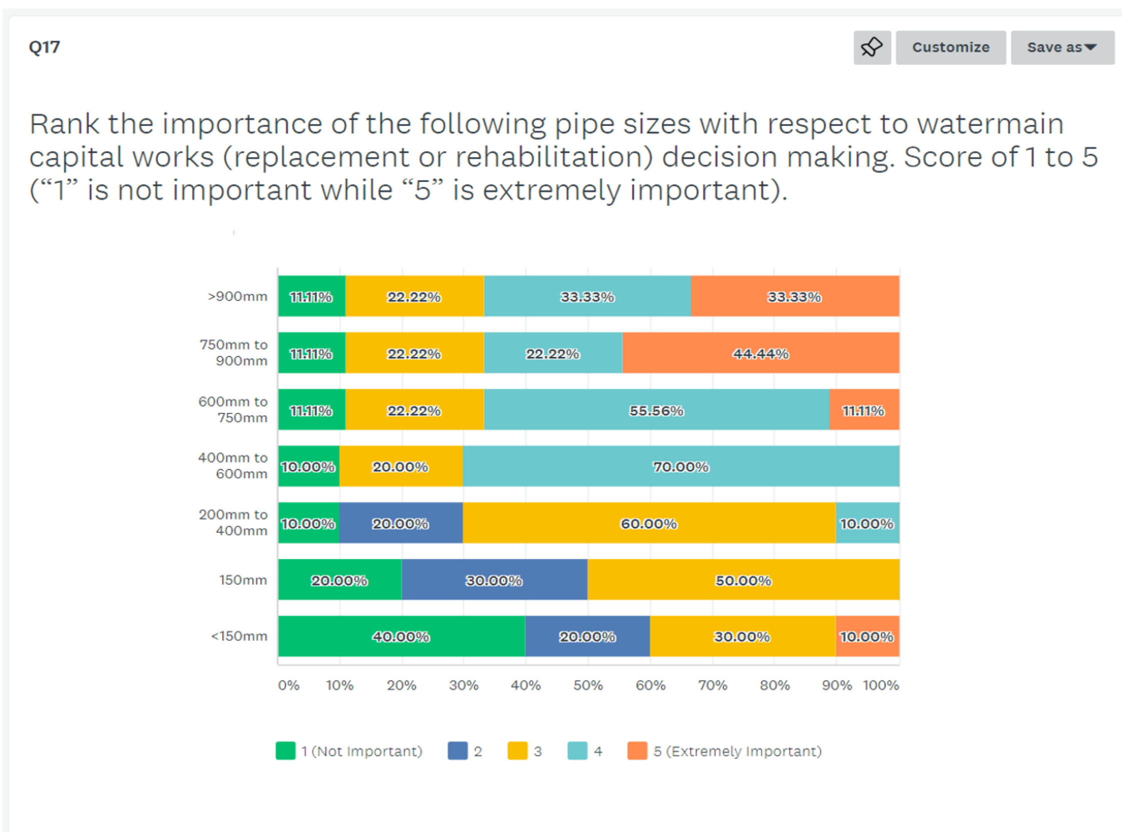
Q15

Customize Save as

Based on your experience, what is the estimated service life for the following pipe materials in corrosive soil conditions?(your answers should be in Years)



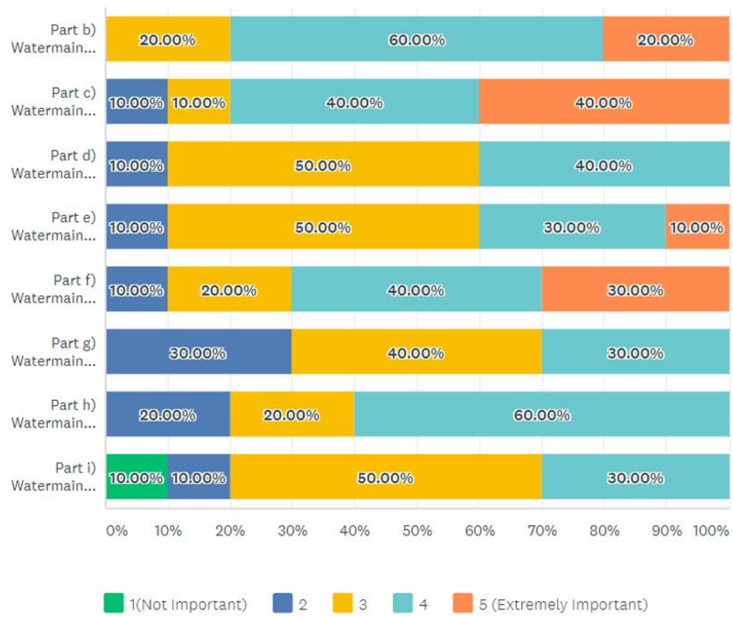

Q16
Customize
Save as
Rank the following watermain quality scenarios with respect to watermain capital works (replacement or rehabilitation) decision making. Score of 1 to 5 ("1" is not important while "5" is extremely important).
Part a) Watermain wi...
Part b) Watermain wi...
Part c) Unlined CI...
Part d) Watermain th...
10.00%
30.00%
30.00%
30.00%
10.00%
40.00%
20.00%
30.00%
22.22%
33.33%
33.33%
11.11%
10.00%
30.00%
10.00%
30.00%
20.00%
0%
10%
20%
30%
40%
50%
60%
70%
80%
90%
100%
1(Not Important)
2
3
4
5 (Extremely Important)


Q17
Customize
Save as
Rank the importance of the following pipe sizes with respect to watermain capital works (replacement or rehabilitation) decision making. Score of 1 to 5 ("1" is not important while "5" is extremely important).
>900mm
750mm to 900mm
600mm to 750mm
400mm to 600mm
200mm to 400mm
150mm
<150mm
11.11%
22.22%
33.33%
33.33%
11.11%
22.22%
22.22%
44.44%
11.11%
22.22%
55.56%
11.11%
10.00%
20.00%
70.00%
10.00%
20.00%
60.00%
10.00%
20.00%
30.00%
50.00%
40.00%
20.00%
30.00%
10.00%
0%
10%
20%
30%
40%
50%
60%
70%
80%
90%
100%
1 (Not Important)
2
3
4
5 (Extremely Important)

Q18

Customize | Save as

Part a) Rank the importance of the following pipe locations for watermain capital works (replacement or rehabilitation) prioritization. Score of 1 to 5 ("1" is not important while "5" is extremely important).



Q19

Save as

List any other possible factors that cause pipe location to be an important issue for watermain capital works (replacement or rehabilitation) decision making.

RESPONSES (1) WORD CLOUD TAGS (0)

Sentiments: OFF

Apply to selected | Filter by tag | Search responses

Showing **1** response

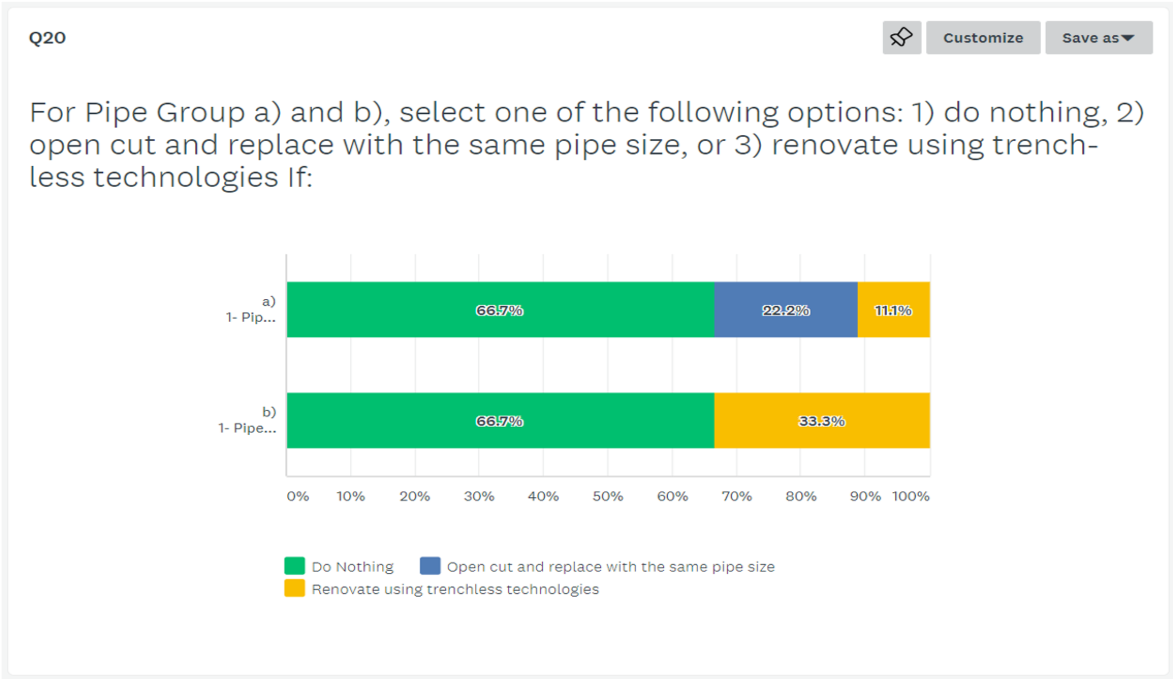
proximity to planned works

5/11/2017 11:50 AM

View respondent's answers | Add tags

A 2.3 Results Part III - Mitigation Model Target Classes

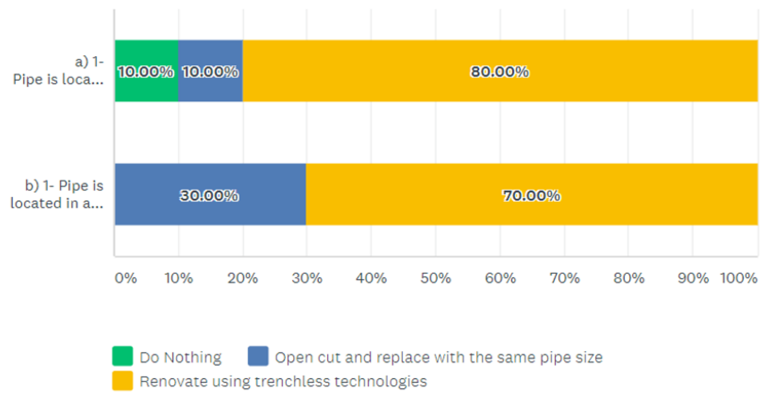
This section of the survey is designed to captured expert's opinion for capital decision based on different pipe scenario using the classes mentioned in section II.



Q21

Customize Save as

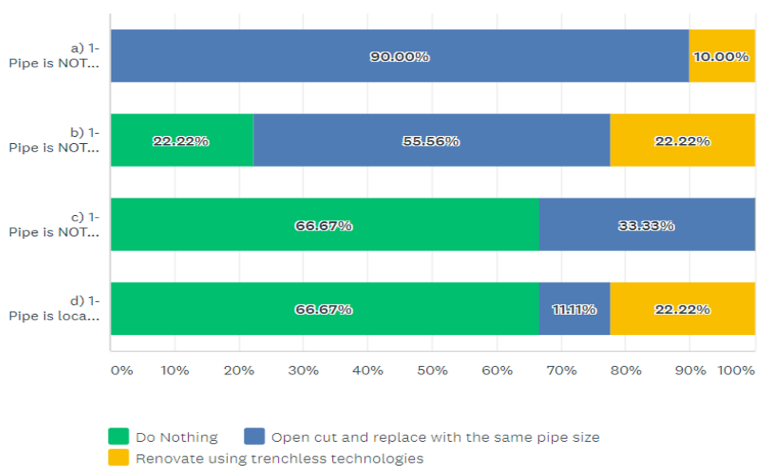
For Pipe Group a) and b), select one of the following options: 1) do nothing, 2) open cut and replace with the same pipe size, or 3) renovate using trench-less technologies If:



Q22

Customize Save as

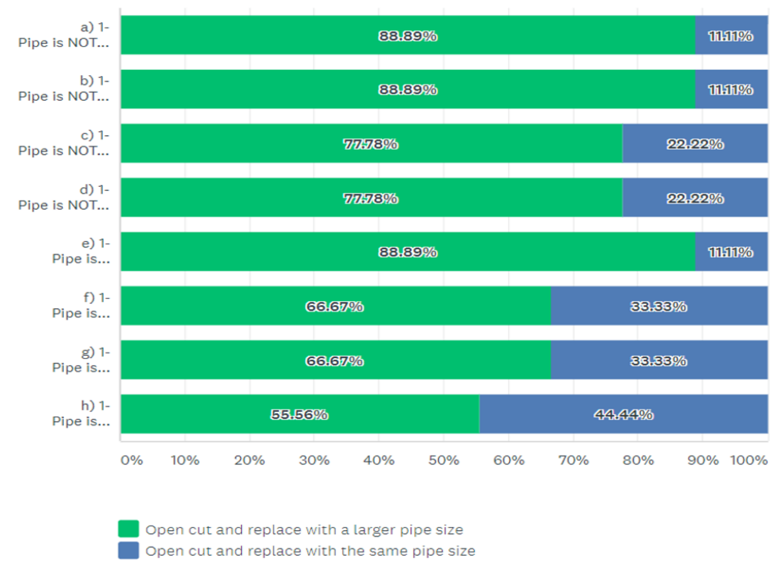
For Pipe Group a) to d), select one of the following options: 1) do nothing, 2) open cut and replace with the same pipe size, or 3) renovate using trench-less technologies, If:



Q23

Customize Save as

What would be the appropriate capital works mitigation plan: 1) “open cut and replace with a larger pipe size”, or 2) “open cut and replace with the same pipe size” If:



Appendix B
ArcGIS Attribute Table, ArcGIS Figures and London Data

B 1 Appendix B1 - Data in ArcGIS Attribute Table

The below table is colour-coded yellow cells containing information for Condition Model. Green cells contained information regarding the Criticality Model. Blue cells contained information used in the Performance Model, and Red cells representing information used in the Mitigation Model. White cells are containing information that is used in more than one model.

	Column Title	Information Contained in this Column	Model	Data Source
1	FID	Unique ID number for every pipe	General	Assigned consecutive number starting 1
2	Shape	Line, Point, Shape	General	Water Main System shapefile
3	OBJECT ID	Pipe ID	General	Water Main System shapefile
4	GIS_Featur	Longitude and latitude information - GIS coordination	General	Water Main System shapefile
5	FRM_NOD E	Starting Pipe Node	General	Water Main System shapefile
6	TO_NODE	Ending Pipe Node	General	Water Main System shapefile
7	StreetNum b	Pipe location Street number	General	Water Main System shapefile
8	StreetName	Pipe location Street name	General	Water Main System shapefile
9	StreetFrom	Pipe location starting point Street name	General	Water Main System shapefile
10	StreetTo	Pipe location ending point Street name	General	Water Main System shapefile
11	TEXTLAB EL	Pipe Label show is surface - diameter mm	General	Water Main System shapefile
12	Rehabilita	Have this Pipe being Rehabilitated in Past - Binary Value	This information used to assess the Mitigation Result	Water Capital Project Excel Sheet
13	MATERIA L	Pipe Material	Condition	Water Main System shapefile

14	Mat_Fact	Material Factor Effecting Pipe Remaining Service Life	Condition	Used Values Recommended by Estimated Material Service Life of Drainage Pipe, 2016
15	TARGET_ Mat_Fact	Material Factor Effecting Pipe Age from Survey Result	Condition	Survey Result
16	Age	Pipe Age	Condition	Simple Calculation of Current Year subtracting Installation year
17	RSL	Remaining Service Live of each Pipe	Condition	Calculated using Equation 2-3 from Chapter 2
18	TARGET_ RSL	Remaining Service Live of each Pipe based on Survey Result	Condition	Survey Result
19	INSTALL_ DA	Pipe Installation Date	Condition	Water Main System shapefile
20	Operation_ Cost	Cost of operating Pipe for Remaining Service Life in present value - Calculated by Operation Unit cost in 2016	Condition	Calculated using 2017 unit rate from Ontario Management and Planning Manual - Capital and Operational Cost Section
21	Maintenanc e_Cost	Maintenance cost of the pipe for Remaining Service Life in present value - Calculated with maintenance unit cost in 2016	Condition	Calculated using 2017 unit rate from Ontario Management and Planning Manual - Capital and Operational Cost Section
22	REPLC_C OST	Replacement cost of the pipe in present value - calculated with replacement cost unit rate 2016	Condition	Calculated using 2017 unit rate from Ontario Management and Planning Manual - Capital and Operational Cost Section
23	MI	Maintenance Index	Condition	Calculated using Equation 2-4 in Chapter 2

24	INST_YR	Pipe Installation Year	Condition	Water Main System shapefile
25	TotBrks	Total Number of Breaks experienced by this pipe	Condition	Water Main Breaks History shapefile
26	BRKS_FV YRS	Number of Breaks each Pipe experienced during recent 5 years	Condition	Water Main Breaks History shapefile
27	Condition_ Score	Total Condition Score	Condition	Calculated using Equation 2-2 in Chapter 2
28	TARGET_ Condition_ Score	Total Condition Score based on Survey Result	Condition	Survey Result
29	Condition_ Score_Leve l	Condition Categories from assumed scores (Very Poor, Poor, Medium, Good, Very Good)	Condition	Condition Classifiers Categories
30	TARGET_ Condition_ Score_Leve l	Condition Categories from Survey Results and Target scores (Very Bad, Bad, Medium, Good, Very Good)	Condition	Survey Result
31	Condition_l evel	Condition Categories from assumed scores (1, 2, 3, 4, and 5)	Condition	Condition Classifiers numeric Values
32	TARGET_ Condition_l evel	Condition Categories from Survey Results and Target scores (1, 2, 3, 4, and 5)	Condition	Survey Result
33	TotBrks	Pipe number of pipe break	Condition	Water Main Breaks History shapefile
34	SOIL	Soil Type	Condition	Soil Data shapefile
35	CorrosionP	Soil Corrosion Factor affecting Pipe Service Life	Condition	Used values recommended by Environmental Chemistry Letters, 2017
36	LEN_M	Pipe Length	Condition	Water Main System shapefile
37	RSL_SCR	Remaining Service Life Score	Condition - Mitigation	Assigned Value Using Table 2-2 in Chapter 2
38	TARGET_ RSL_SCR	Remaining Service Life Score calculated from survey result	Condition - Mitigation	Survey Result
39	MI_SCR	Maintenance Index Score	Condition - Mitigation	Assigned score using Table 2-6 in Chapter 2

40	BRK_SCR	Break score for number of breaks that this pipe experienced	Condition - Mitigation	Assigned a value using Table 2-4in Chapter 2
41	BRK_SCR _TARGET	Total Break Score from Survey Result	Condition - Mitigation	Survey Result
42	BRKS_FV YRS_SCR	Break score for number of breaks that this pipe experienced in recent 5 years	Condition - Mitigation	Assigned a value using Table 2-5 in Chapter 2
43	BRKS_FV YRS_SCR _TARGET	Recent 5 years Breaks scores from Survey Result	Condition - Mitigation	Survey Result
44	condition_ model_pred	Condition Categories from Survey Results and Target scores (1, 2, 3, 4, and 5)	Condition Result	Model Generated Values
45	DIAMETE R	Pipe Diameter	Condition , Criticality and Performance	Water Main System shapefile
46	Diameter Category	Diameter category according to model organization explained in PAN Chapter	Condition , Criticality and Performance	Assigned score from Table 2-10 in Chapter 2
47	TRANS	Is this pipe a transmission pipe	Criticality	Gathered information from different sources, mostly from Water System Shapefile
48	WaterBodi e	Is this pipe crossing a water body - Binary Value	Criticality	Base Maps shapefile
49	Under Bridger	Is this pipe crossing a bridge - Binary value	Criticality	Base Maps shapefile
50	RoadWay	Is this pipe within right of way - Binary Value	Criticality	Base Maps shapefile
51	Forest_Gre	Is this pipe crossing Forest or Green belt - Binary Value	Criticality	Base Maps shapefile
52	River_cree	Is this pipe crossing creek or river - Binary Value	Criticality	Base Maps shapefile
53	LandFill	Is this pipe crossing a landfill area - Binary Value	Criticality	Base Maps shapefile
54	WL	Is this pipe crossing a Wet Land - Binary Value	Criticality	Base Maps shapefile
55	HWY	Is this Pipe crossing Highway - Binary Value	Criticality	Base Maps shapefile
56	RWY	Is this pipe crossing Rail Way - Binary Value	Criticality	Base Maps shapefile
57	Easement	Assessing this pipe require an easement - Binary Value	Criticality	Pubic Properties and Easement information Excel Sheets

58	EasementLo	Is required easement granted by Municipality - Binary Value	Criticality	Pubic Properties and Easement information Excel Sheets
59	RoadClass	What is the Road Class of the pipe location - how important is this pipe	Criticality	Road Closer and Road Moratorium Information
60	HydrantCon	Is this pipe connecting to a Fire Hydrant - Binary Value	Criticality	Gathered information from different sources, mostly from Water System Shapefile
61	PipeLocati	Is this pipe providing service to Critical Location - Binary Value	Criticality	Critical Location shapefile
62	ImportantC	Is this pipe providing service to important location - Binary Value	Criticality	Critical Location shapefile
63	Medical_Services	Is this pipe providing service to medical building - Binary Value	Criticality	Critical Location shapefile
64	NEW_DEVELO	Is this pipe providing service to a new development - Binary Value	Criticality	New Development Information
65	Development	Is this pipe providing service to a new development - Binary Value	Criticality	New Development Information
66	Criticality_SCR	Total Criticality score	Criticality	Calculated using Equasion 2-7 in Chapter 2
67	TARGET_Criticality_SCR	Total criticality score from survey results and target values	Criticality	Calculated Using Equasion 2-7 in Chapter 2 using target values
68	Criticality_Score_Level	Criticality categories based on assumed scores (Very High, Moderately High, Medium, Moderately Low, Very Low)	Criticality	Criticality Classifiers Categories
69	TARGET_Criticality_Score_Level	Criticality categories based on survey result scores (Very High, Moderately High, Medium, Moderately Low, Very Low)	Criticality	Target Criticality Classifiers Categories

70	Criticality_ Level	Criticality Categories from assumed scores (1, 2, 3, 4, and 5)	Criticality	Criticality Classifiers Numeric Values
71	TARGET_ Criticality_ Level	Criticality Categories from survey results (1, 2, 3, 4, and 5)	Criticality	Target Criticality Classifiers Numeric Values
72	DIA_SCR	Diameter Score	Criticality - Mitigation	Assigned score using Table 4-10 in Chapter 2
73	TARGET_ DIA_SCR	Target Diameter scores from survey results	Criticality - Mitigation	Survey Result
74	ENVMT_S CR	Environmental score	Criticality - Mitigation	Assigned score using Table 2-11 in Chapter 2
75	TARGET_ ENVMT_S CR	Target Environmental score from survey result	Criticality - Mitigation	Survey Result
76	ACCESS_ SCR	Accessibility score	Criticality - Mitigation	Assigned score using Table 2-12 in Chapter 2
77	TARGET_ ACCESS_ SCR	Target accessibility score from Survey Result	Criticality - Mitigation	Survey Result
78	criticality_ model_pred	Criticality Model Result (1, 2, 3, 4, and 5)	Criticality Result	Model Generated Values
79	PressureCo mplaints	If there has been any complaint regarding water pressure for this pipe and this location - Binary Value	Performance	Gathered information from different sources mostly excel sheets filled with Operation and maintenance field forms
80	WaterCom plaints	If there has been any complaint regarding this Pipe - Binary Value	Performance	Assigned a value using Table 2-11 in Chapter 2
81	TracerWire	Does this pipe have Tracer Wire - According to standard - Binary Value	Performance	Gathered from several sources such as final as-built drawings and maintenance reports
82	DeadEnd	Does this pipe located at the dead-end - Standard conformance (without a loop) - Binary Value	Performance	Water System Shapefile

83	STANDARD_CONFOR R	Is this pipe conforming the latest standard for material and size,,,,	Performance	Assigned a value using Table 2-9 in Chapter 2
84	f	Pipe material friction roughness value	Performance	Used values recommended by Fluid Mechanics for Engineers By David A. Chin, 2017
85	R	Pipe Length divided by Pipe Diameter	Performance	Simple calculation of dividing pipe length by pipe diameter
86	HL	Head Loss calculated based on the pipe material, diameter, pipe length according to the Darcy-Weisbach equation	Performance	Calculated using Darcy–Weisbach equation
87	Performanc _SCR	Total Performance score	Performance	Calculated using Equation 2-5 in Chapter 2
88	TARGET_ Performanc _SCR	Total Performance score based on Target values from survey results	Performance	Survey Result
89	Performance_Score_Level	Performance Categories based on assumed score (Very Poor, Poor, Moderate, Good, Very Good)	Performance	Performance Classifiers Categories
90	TARGET_ Performance_Score_Level	Performance Categories based on survey result score (Very Poor, Poor, Moderate, Good, Very Good)	Performance	Target Performance Classifiers Categories
91	Performance_Level	Performance Categories from assumed scores (1, 2, 3, 4, and 5)	Performance	Performance Classifiers Numeric Values
92	TARGET_ Performance_Level	Performance Categories from survey results (1, 2, 3, 4, and 5)	Performance	Target Performance Classifiers Numeric Values
93	HEAD_LOSS_SCR	Head Loss score	Performance - Mitigation	Assigned a value using Table 2-6 in Chapter 2

94	QUALIT_SCR	Water Quality score	Performance - Mitigation	Assigned value using Table 2-7 in Chapter 2
95	TARGET_QUALIT_SCR	Water Quality score based on survey result	Performance - Mitigation	Survey Result
96	performance_model_pred	Performance Model Result (1, 2, 3, 4, and)	Performance Results	Model Generated Values
97	PAN	Total Priority Action Number scores	Mitigation	Calculated Using Equation 2-1 in Chapter 2
98	TARGET_PAN	Total Priority Action Number from survey results	Mitigation	Calculated Using Equation 2-1 in Chapter 2 with Target values
99	MITIGATION_Score_Level	Mitigation levels based on PAN (Do Nothing, Repair and Renovate, Replace, and Upsize)	Mitigation	PAN Classifiers Categories
100	TARGET_MITIGATION_Score_Level	Mitigation levels based on Target PAN from survey results (Do Nothing, Repair and Renovate, Replace, and Upsize)	Mitigation	Target PAN Classifiers Categories
101	MITIGATION_Level_PAN	Mitigation Categories from PAN (1, 2, 3, and 4)	Mitigation	PAN Classifiers Numeric Values
102	TARGET_MITIGATION_Level_PAN	Mitigation Categories from Target PAN (1, 2, 3, and 4)	Mitigation	Target PAN Classifiers Numeric Values
103	mitigation_model_pred	Mitigation Model Results (1, 2, 3, and 4)	Mitigation Result	Model Generated Values
104	Mitigation_Model_Level	Mitigation Model Results (Do Nothing, Repair and Renovate, Replace, and Upsize)	Mitigation Result	Model Generated Values

B 2 Appendix B2 - ArcGIS Figures

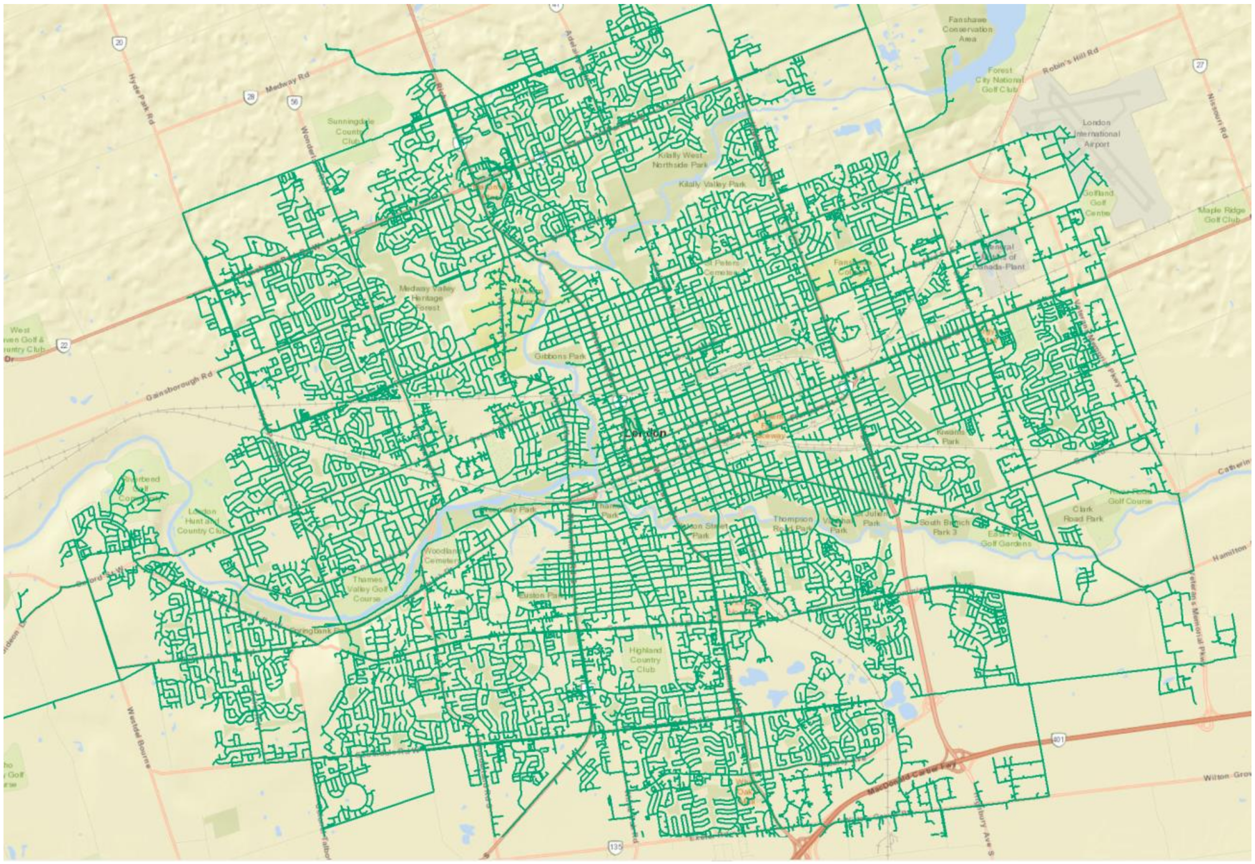


Figure B2-1 City of London Water Network System Shapefile

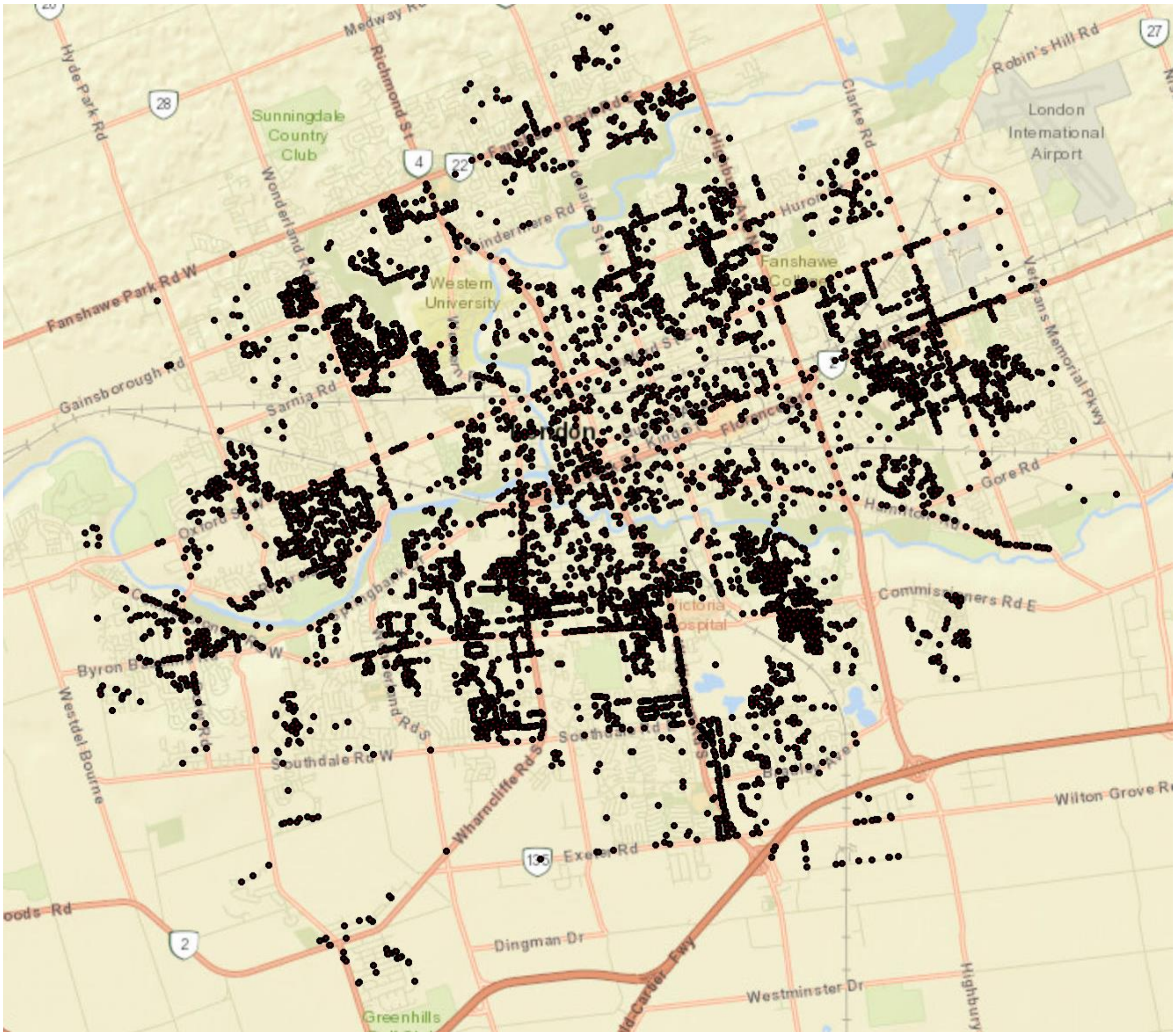


Figure B2-2 City of London Break Data Point file

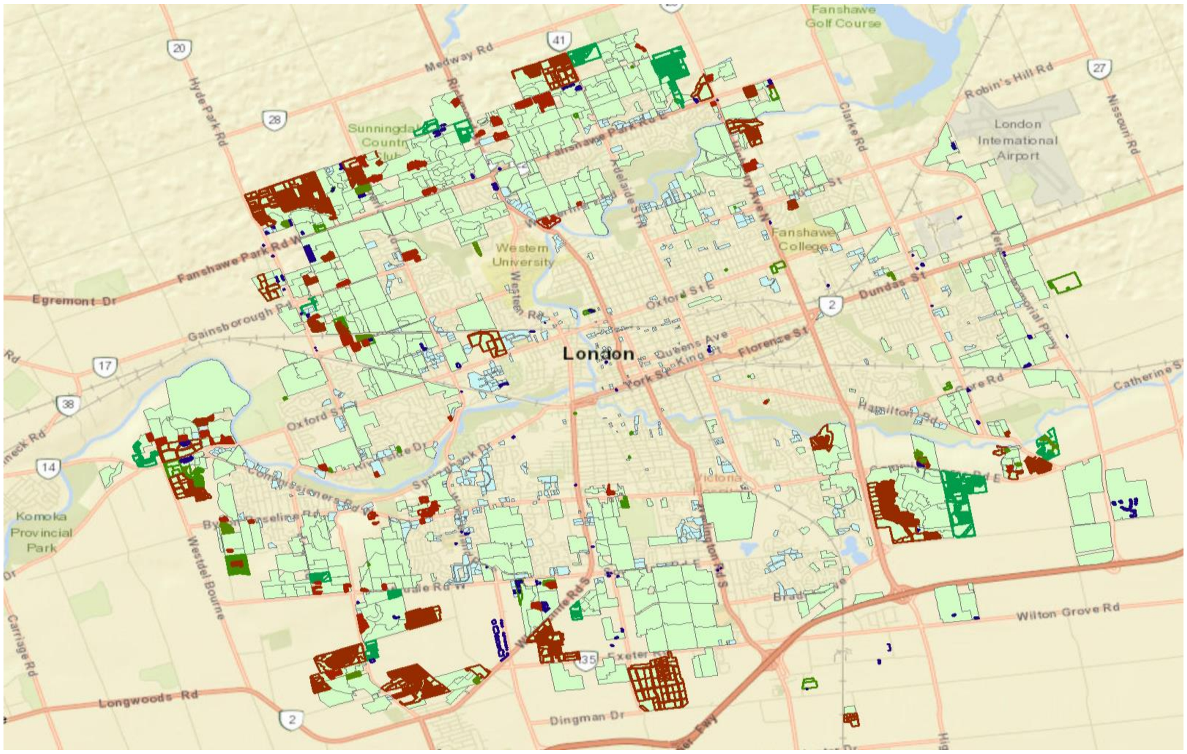


Figure B2-3 Development and Condo proposal location Shapefile

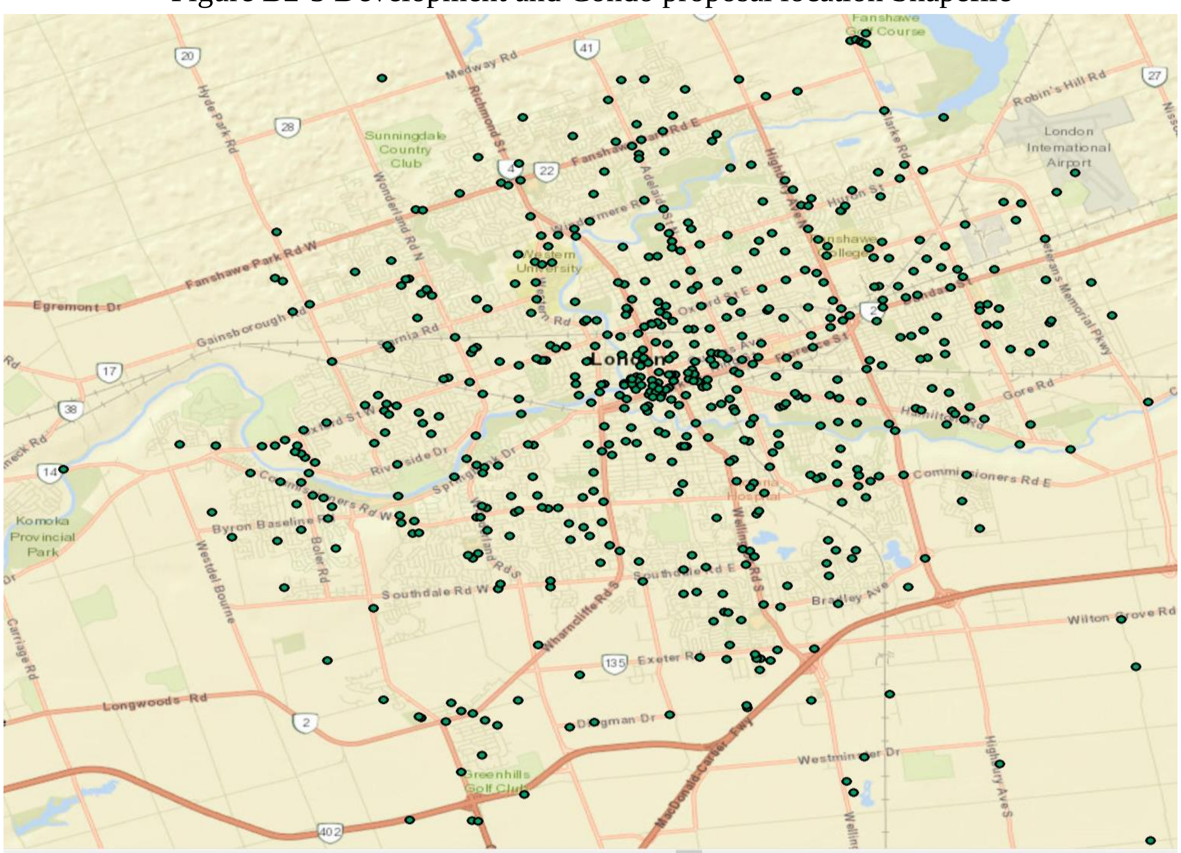


Figure B2-4 Critical Service Locations Shapefile

Table

final

WaterBodie	Under_Bridger	RoadWay	Forest_Gre	River_cree	LandFill	WL	HWY	RWY	TracerWire_1	Rehabilita_1	Easement
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	1	0	0
0	0	1	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	1	0	0
0	0	0	0	0	0	0	0	0	1	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	1	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	1	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	1	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	1	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	1	0	0
0	0	0	0	0	0	0	0	0	1	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	1	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	1	0	0	0	0	0	0	1	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	1	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	1	0	0
0	0	0	0	0	0	0	0	0	1	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	1	0
0	0	0	0	0	0	0	0	0	0	0	0

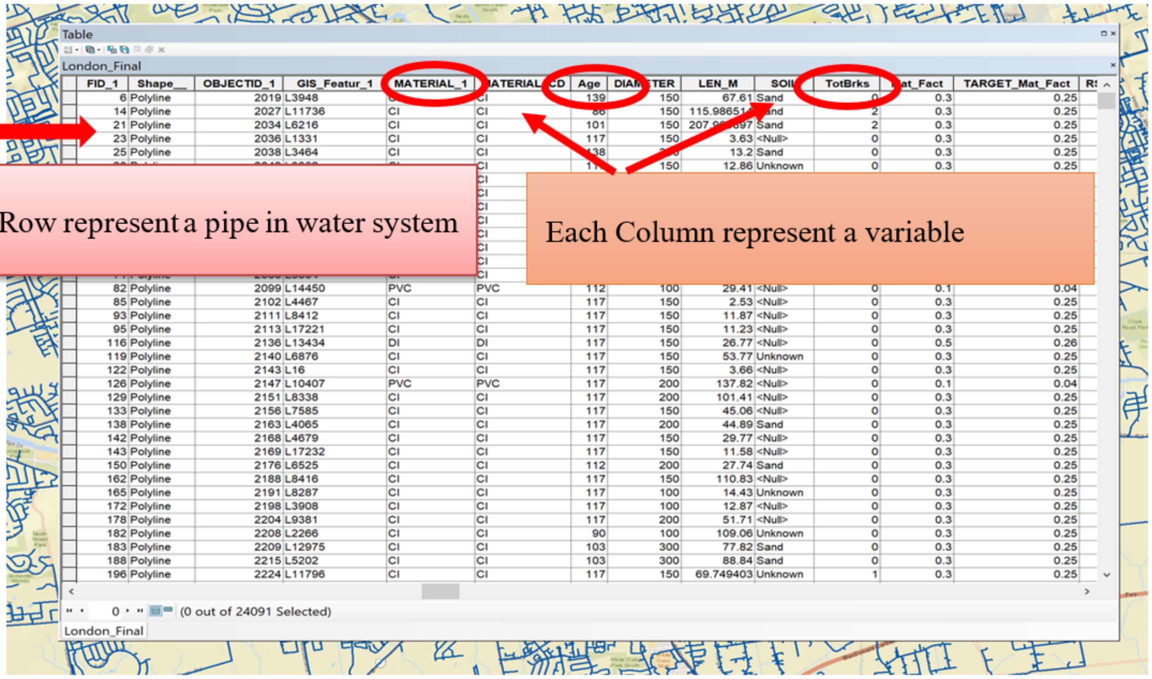
FigureB2-5 Binary Values

Table

final

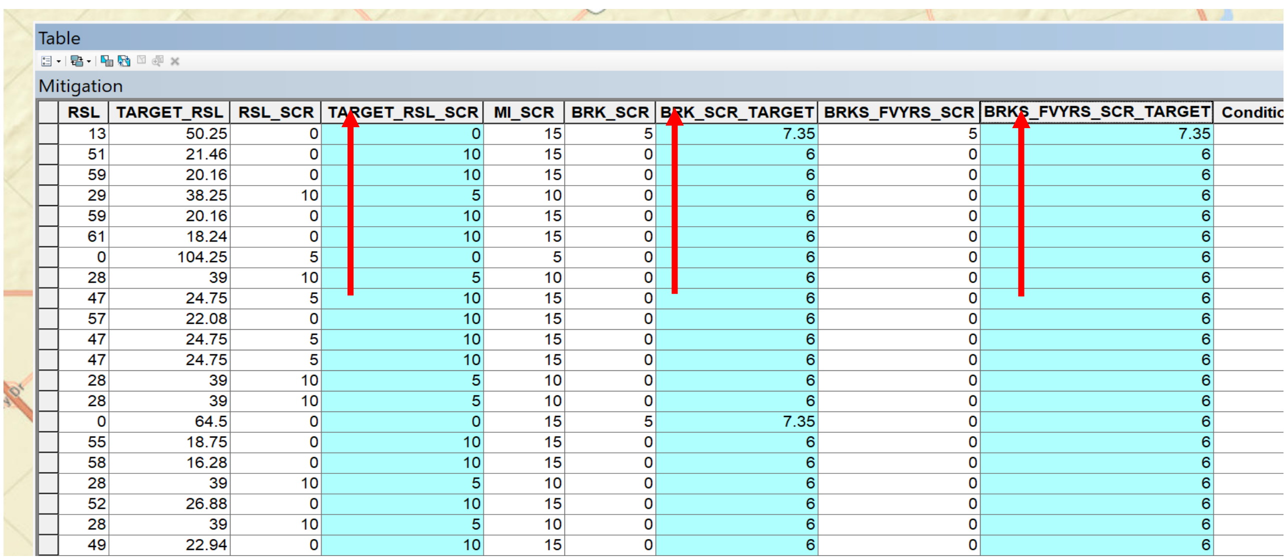
DeadEnd_1	RoadClass_1	HydrantCon_1	PipeLocati_1	ImportantC_1	CorrosionP_1	Medical_Services
0	1	1	1	1	0	0
0	0	0	0	0	0	0
0	2	1	1	1	0	0
0	2	0	1	1	0	1
0	1	0	1	1	0	0
0	0	0	0	0	0	0
0	3	0	1	1	0	0
0	0	0	1	1	0	1
0	0	0	1	1	0	1
0	1	0	1	1	0	0
0	0	0	1	1	0	1
0	0	0	1	1	0	1
0	0	0	1	1	0	1
0	0	0	1	1	0	1
0	1	1	1	1	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	1	1	0	1
1	1	0	1	1	0	0
0	0	0	1	1	0	0
1	1	0	1	1	0	0
1	1	1	1	1	0	0
1	1	0	1	1	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	1	0	1	1	0	1
0	2	0	1	1	0	0
0	1	1	1	1	0	0
0	1	0	1	1	0	0
0	0	0	0	0	0	1
0	1	0	1	1	0	0
0	2	0	1	1	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	1	1	1	1	0	0
0	0	0	0	0	0	0
0	3	0	1	1	0	0

Figure B2-6 Binary Value showing Critical Location



FID_1	Shape_	OBJECTID_1	GIS_Featur_1	MATERIAL_1	MATERIAL_CD	Age	DIAMETER	LEN_M	SOIL	TotBrks	Mat_Fact	TARGET_Mat_Fact
6	Polyline	2019	L3948	[illegible]	CI	139	150	67.61	Sand	0	0.3	0.25
14	Polyline	2027	L11736	CI	CI	86	150	115.98651	[illegible]	2	0.3	0.25
21	Polyline	2034	L6216	CI	CI	101	150	[illegible]	Sand	2	0.3	0.25
23	Polyline	2036	L1331	CI	CI	117	150	3.63	<Null>	0	0.3	0.25
25	Polyline	2038	L3464	CI	CI	138	[illegible]	13.2	Sand	0	0.3	0.25
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	CI	[illegible]	150	12.86	Unknown	0	0.3	0.25
					CI							
					CI							
					CI							
					CI							
					CI							
					CI							
					CI							
					CI							
82	Polyline	2099	L14450	PVC	PVC	112	100	29.41	<Null>	0	0.1	0.04
85	Polyline	2102	L4467	CI	CI	117	150	2.53	<Null>	0	0.3	0.25
93	Polyline	2111	L8412	CI	CI	117	150	11.87	<Null>	0	0.3	0.25
95	Polyline	2113	L17221	CI	CI	117	150	11.23	<Null>	0	0.3	0.25
116	Polyline	2136	L13434	DI	DI	117	150	26.77	<Null>	0	0.5	0.26
119	Polyline	2140	L6876	CI	CI	117	150	53.77	Unknown	0	0.3	0.25
122	Polyline	2143	L16	CI	CI	117	150	3.66	<Null>	0	0.3	0.25
126	Polyline	2147	L10407	PVC	PVC	117	200	137.82	<Null>	0	0.1	0.04
129	Polyline	2151	L8338	CI	CI	117	200	101.41	<Null>	0	0.3	0.25
133	Polyline	2156	L7585	CI	CI	117	150	45.06	<Null>	0	0.3	0.25
138	Polyline	2163	L4065	CI	CI	117	200	44.89	Sand	0	0.3	0.25
142	Polyline	2168	L4679	CI	CI	117	150	29.77	<Null>	0	0.3	0.25
143	Polyline	2169	L17232	CI	CI	117	150	11.58	<Null>	0	0.3	0.25
150	Polyline	2176	L6525	CI	CI	112	200	27.74	Sand	0	0.3	0.25
162	Polyline	2188	L8416	CI	CI	117	150	110.83	<Null>	0	0.3	0.25
165	Polyline	2191	L8287	CI	CI	117	100	14.43	Unknown	0	0.3	0.25
172	Polyline	2198	L3908	CI	CI	117	100	12.87	<Null>	0	0.3	0.25
178	Polyline	2204	L9381	CI	CI	117	200	51.71	<Null>	0	0.3	0.25
182	Polyline	2208	L2266	CI	CI	90	100	109.06	Unknown	0	0.3	0.25
183	Polyline	2209	L12975	CI	CI	103	300	77.82	Sand	0	0.3	0.25
188	Polyline	2215	L5202	CI	CI	103	300	88.84	Sand	0	0.3	0.25
196	Polyline	2224	L11796	CI	CI	117	150	69.749403	Unknown	1	0.3	0.25

Figure B2-7 Variable and Data information in ArcGIS



RSL	TARGET_RSL	RSL_SCR	TARGET_RSL_SCR	MI_SCR	BRK_SCR	BRK_SCR_TARGET	BRKS_FVYRS_SCR	BRKS_FVYRS_SCR_TARGET	Conditic
13	50.25	0	0	15	5	7.35	5	7.35	
51	21.46	0	10	15	0	6	0	6	
59	20.16	0	10	15	0	6	0	6	
29	38.25	10	5	10	0	6	0	6	
59	20.16	0	10	15	0	6	0	6	
61	18.24	0	10	15	0	6	0	6	
0	104.25	5	0	5	0	6	0	6	
28	39	10	5	10	0	6	0	6	
47	24.75	5	10	15	0	6	0	6	
57	22.08	0	10	15	0	6	0	6	
47	24.75	5	10	15	0	6	0	6	
47	24.75	5	10	15	0	6	0	6	
28	39	10	5	10	0	6	0	6	
28	39	10	5	10	0	6	0	6	
0	64.5	0	0	15	5	7.35	0	6	
55	18.75	0	10	15	0	6	0	6	
58	16.28	0	10	15	0	6	0	6	
28	39	10	5	10	0	6	0	6	
52	26.88	0	10	15	0	6	0	6	
28	39	10	5	10	0	6	0	6	
49	22.94	0	10	15	0	6	0	6	

Figure B2-8 Target values are from Survey Results

_RSL	RSL_SCR	TARGET_RSL_SCR	MI_SCR	BRK_SCR	BRK_SCR_TARGET	BRKS_FVYRS_SCR	BRKS_FVYRS_SCR_TARGET
26.88	0	10	15	0	6	0	6
39	10	5	10	0	6	0	6
22.94	0	10	15	0	6	0	6
75.75	5	0	15	0	6	5	7.35
34.04	0	5	15	0	6	5	7.35
87.75	5	0	15	0	6	0	6
14.4	0	15	15	0	6	0	6
103.5	5	0	5	0	6	0	6
22.08	0	10	15	0	6	0	6
26.88	0	10	15	0	6	0	6
29.6	0	10	15	0	6	0	6
87.75	5	0	15	0	6	0	6
22.2	0	10	15	0	6	0	6
21.12	0	10	15	0	6	0	6
87.75	5	0	15	0	6	0	6
51	0	0	15	0	6	0	6
22.5	0	10	15	0	6	0	6
26.88	0	10	15	0	6	0	6
23.04	0	10	15	0	6	0	6
87.75	5	0	15	0	6	0	6
73.5	0	0	15	0	6	0	6
87.75	5	0	15	0	6	0	6

Figure B2-9 Variables for Condition Model

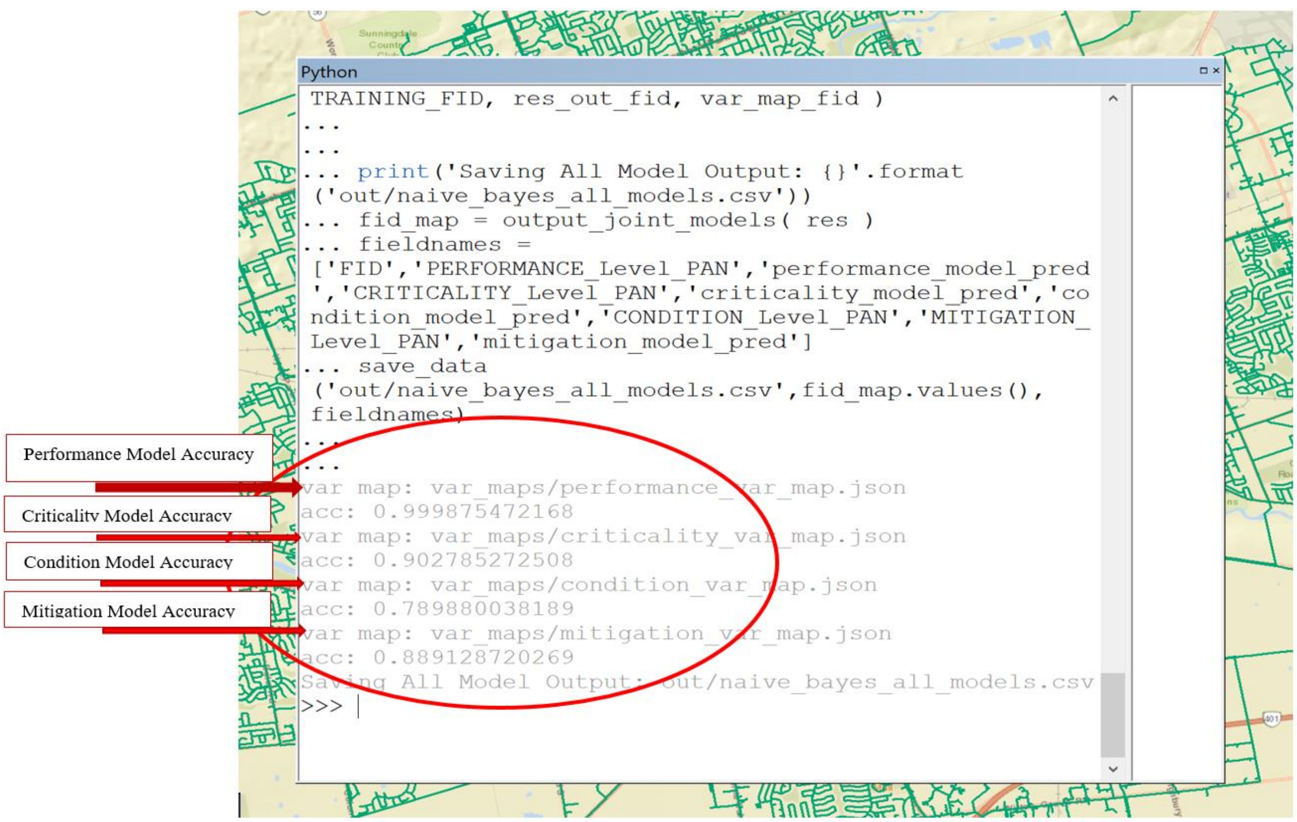
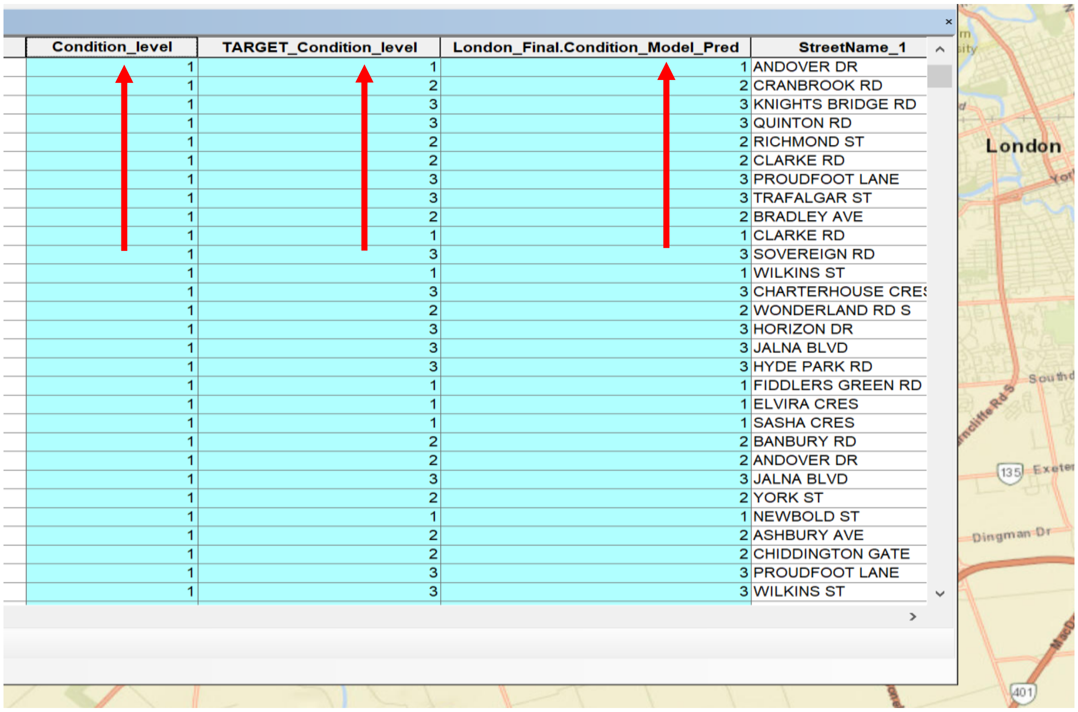


Figure B2-10 All Models Results



Condition_level	TARGET_Condition_level	London_Final.Condition_Model_Pred	StreetName_1
1	1	1	ANDOVER DR
1	2	2	CRANBROOK RD
1	3	3	KNIGHTS BRIDGE RD
1	3	3	QUINTON RD
1	2	2	RICHMOND ST
1	2	2	CLARKE RD
1	3	3	PROUDFOOT LANE
1	3	3	TRAFALGAR ST
1	2	2	BRADLEY AVE
1	1	1	CLARKE RD
1	3	3	SOVEREIGN RD
1	1	1	WILKINS ST
1	3	3	CHARTERHOUSE CRE
1	2	2	WONDERLAND RD S
1	3	3	HORIZON DR
1	3	3	JALNA BLVD
1	3	3	HYDE PARK RD
1	1	1	FIDDLERS GREEN RD
1	1	1	ELVIRA CRES
1	1	1	SASHA CRES
1	2	2	BANBURY RD
1	2	2	ANDOVER DR
1	3	3	JALNA BLVD
1	2	2	YORK ST
1	1	1	NEWBOLD ST
1	2	2	ASHBURY AVE
1	2	2	CHIDDINGTON GATE
1	3	3	PROUDFOOT LANE
1	3	3	WILKINS ST

Figure B2-11 Assigned Condition Level, Target Condition Level and Model Predicted Condition Level

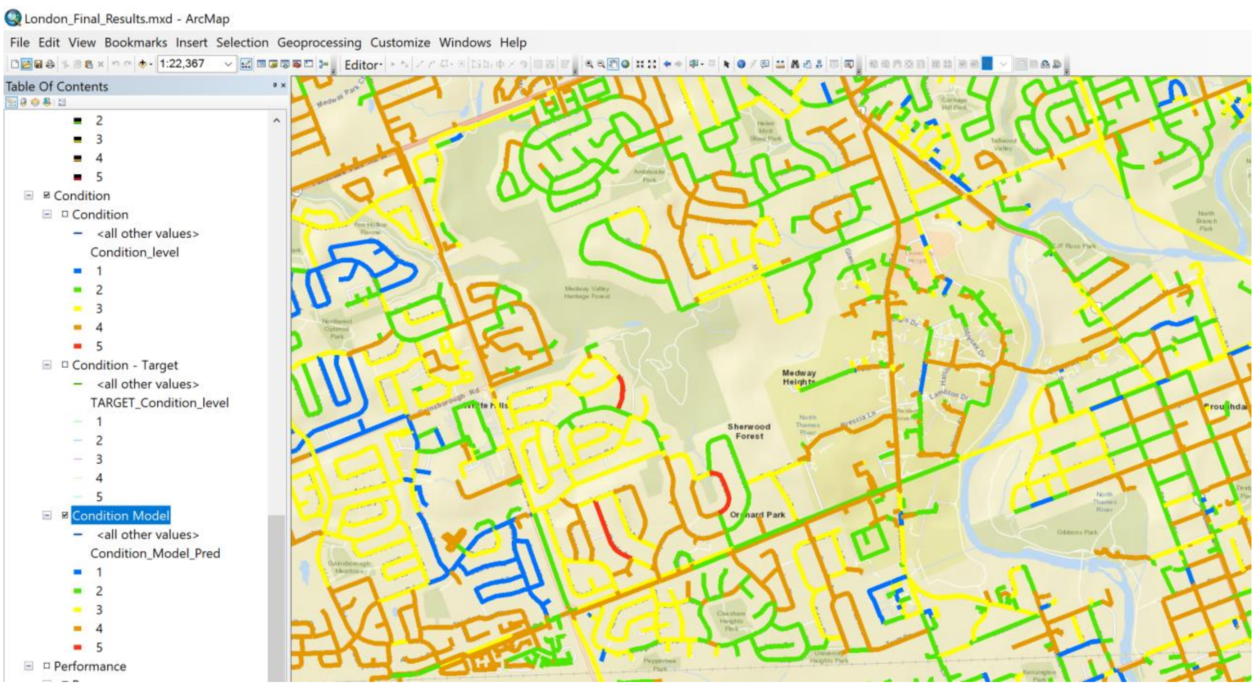
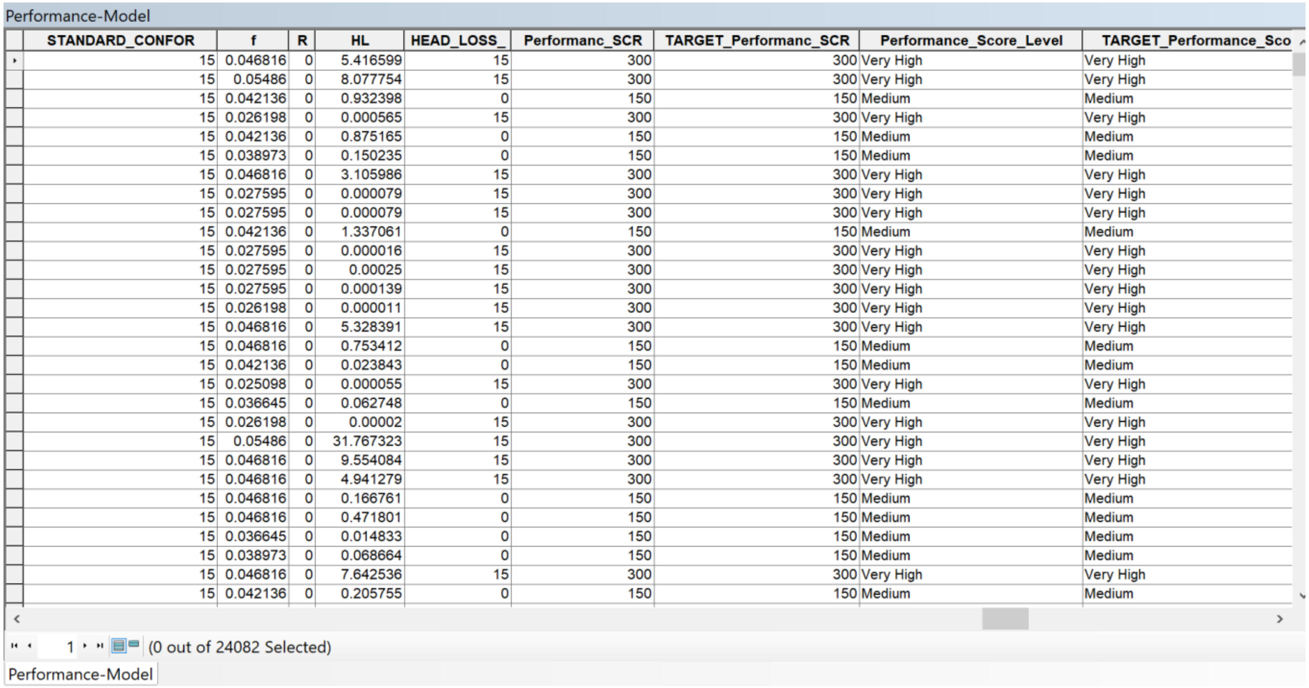


Figure B2-12 Condition Categories in ArcGIS Interface



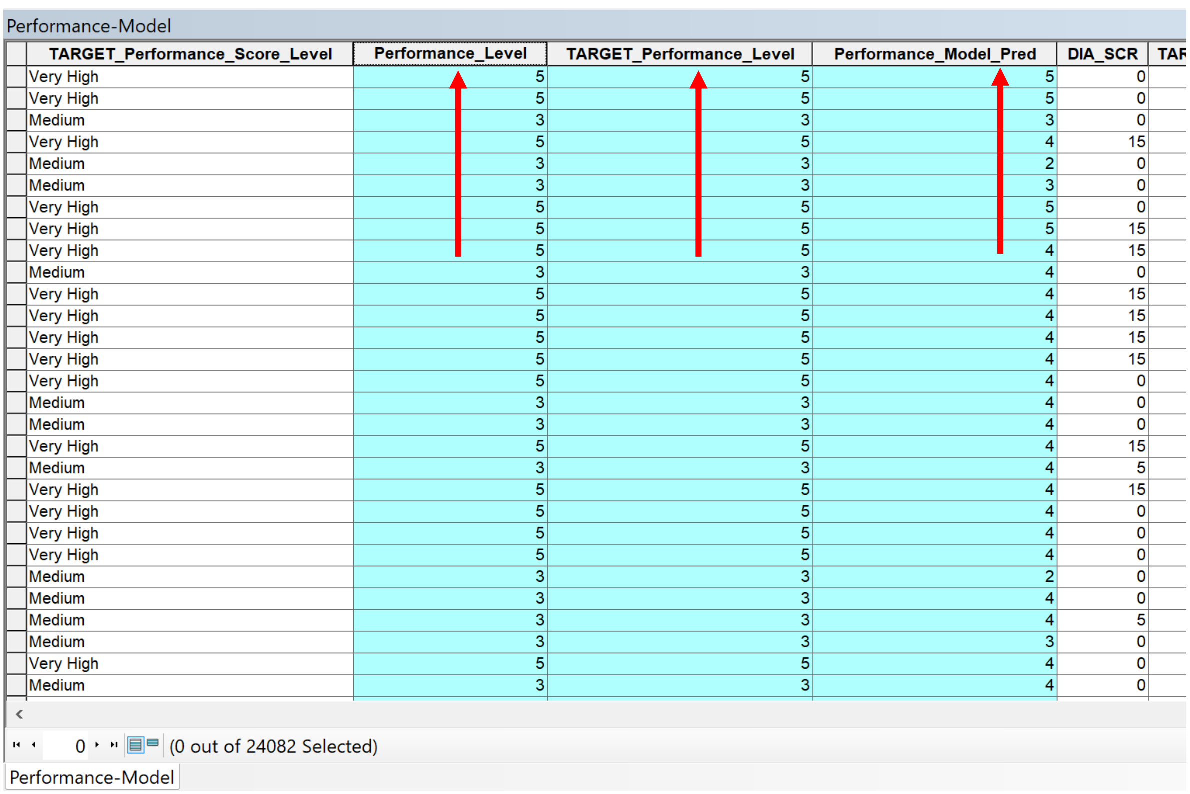
Performance-Model

STANDARD_CONFOR	f	R	HL	HEAD_LOSS_	Performanc_SCR	TARGET_Performanc_SCR	Performance_Score_Level	TARGET_Performance_Sco
15	0.046816	0	5.416599	15	300	300	Very High	Very High
15	0.05486	0	8.077754	15	300	300	Very High	Very High
15	0.042136	0	0.932398	0	150	150	Medium	Medium
15	0.026198	0	0.000565	15	300	300	Very High	Very High
15	0.042136	0	0.875165	0	150	150	Medium	Medium
15	0.038973	0	0.150235	0	150	150	Medium	Medium
15	0.046816	0	3.105986	15	300	300	Very High	Very High
15	0.027595	0	0.000079	15	300	300	Very High	Very High
15	0.027595	0	0.000079	15	300	300	Very High	Very High
15	0.042136	0	1.337061	0	150	150	Medium	Medium
15	0.027595	0	0.000016	15	300	300	Very High	Very High
15	0.027595	0	0.00025	15	300	300	Very High	Very High
15	0.027595	0	0.000139	15	300	300	Very High	Very High
15	0.026198	0	0.000011	15	300	300	Very High	Very High
15	0.046816	0	5.328391	15	300	300	Very High	Very High
15	0.046816	0	0.753412	0	150	150	Medium	Medium
15	0.042136	0	0.023843	0	150	150	Medium	Medium
15	0.025098	0	0.000055	15	300	300	Very High	Very High
15	0.036645	0	0.062748	0	150	150	Medium	Medium
15	0.026198	0	0.00002	15	300	300	Very High	Very High
15	0.05486	0	31.767323	15	300	300	Very High	Very High
15	0.046816	0	9.554084	15	300	300	Very High	Very High
15	0.046816	0	4.941279	15	300	300	Very High	Very High
15	0.046816	0	0.166761	0	150	150	Medium	Medium
15	0.046816	0	0.471801	0	150	150	Medium	Medium
15	0.036645	0	0.014833	0	150	150	Medium	Medium
15	0.038973	0	0.068664	0	150	150	Medium	Medium
15	0.046816	0	7.642536	15	300	300	Very High	Very High
15	0.042136	0	0.205755	0	150	150	Medium	Medium

1 (0 out of 24082 Selected)

Performance-Model

Figure B2-13 Performance Variables in ArcGIS Attribute table



Performance-Model

TARGET_Performance_Score_Level	Performance_Level	TARGET_Performance_Level	Performance_Model_Pred	DIA_SCR	TAR
Very High	5	5	5	0	
Very High	5	5	5	0	
Medium	3	3	3	0	
Very High	5	5	4	15	
Medium	3	3	2	0	
Medium	3	3	3	0	
Very High	5	5	5	0	
Very High	5	5	5	15	
Very High	5	5	4	15	
Medium	3	3	4	0	
Very High	5	5	4	15	
Very High	5	5	4	15	
Very High	5	5	4	15	
Very High	5	5	4	15	
Very High	5	5	4	0	
Medium	3	3	4	0	
Medium	3	3	4	0	
Very High	5	5	4	15	
Medium	3	3	4	5	
Very High	5	5	4	15	
Very High	5	5	4	0	
Very High	5	5	4	0	
Very High	5	5	4	0	
Medium	3	3	2	0	
Medium	3	3	4	0	
Medium	3	3	4	5	
Medium	3	3	3	0	
Very High	5	5	4	0	
Medium	3	3	4	0	

0 (0 out of 24082 Selected)

Performance-Model

Figure B2-14 Performance Values in ArcGIS Attribute Table

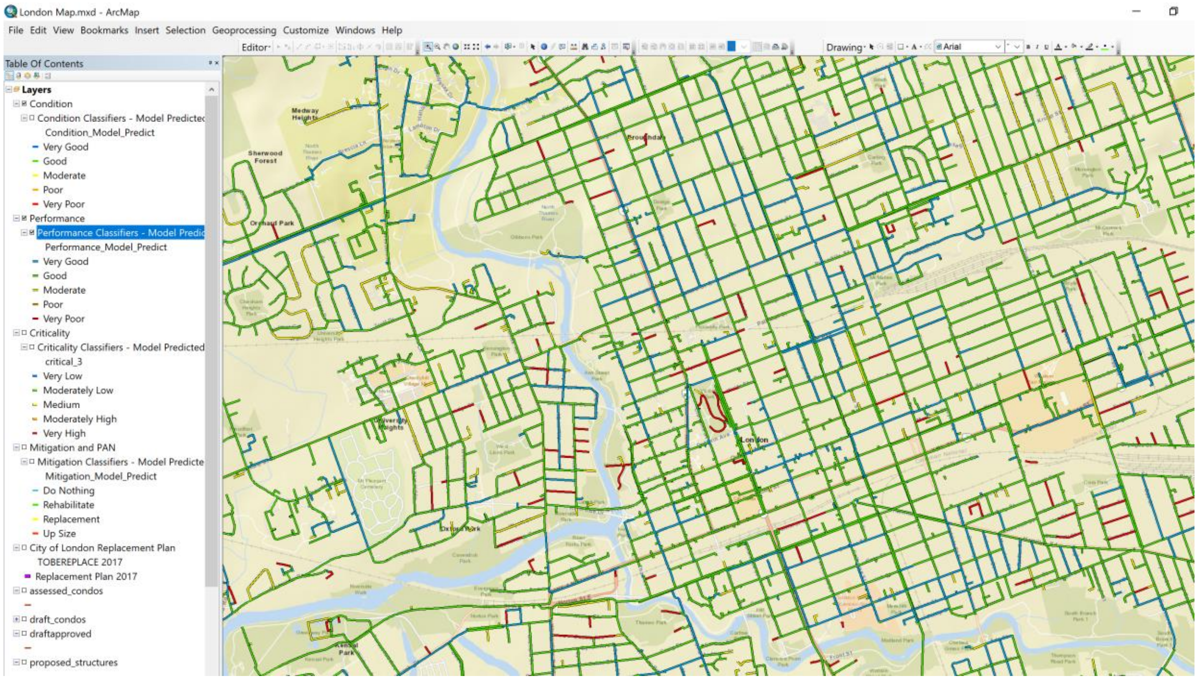
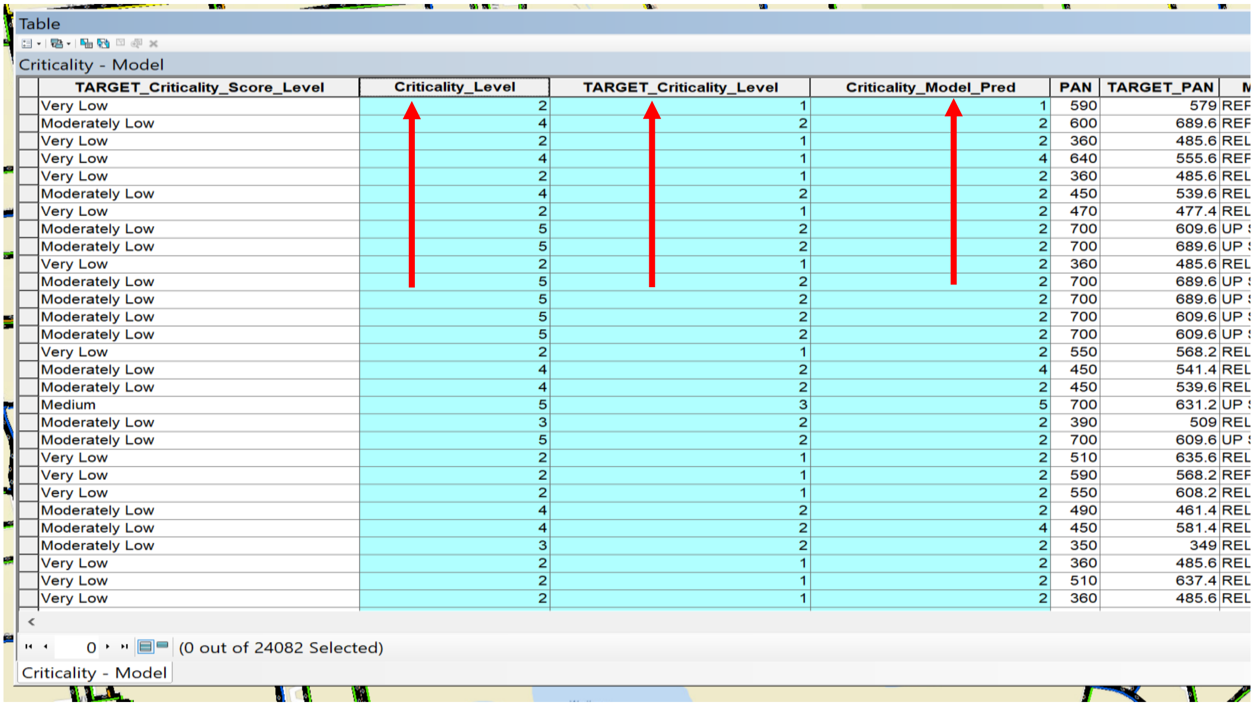


Figure B2-15 Performance Model Result in ArcGIS

WTR	ESA	WL	FLP	HWY	RWY	HPU	HEU	Hospital	Med_Centre	LT_CARE	School	Hosp_Serv	Airp_Serv	H
0	0	0	0	0	0	0	0	0	0	0	0	0	0	
0	0	0	0	0	0	0	0	0	0	0	1	0	0	
0	0	0	0	0	0	0	0	0	0	0	1	0	0	
0	0	0	0	0	0	0	0	0	0	0	1	0	0	
0	0	0	0	0	0	0	0	0	0	0	0	0	0	
0	0	0	0	0	0	0	0	0	0	0	0	0	0	
0	0	0	0	0	0	0	0	0	0	0	0	0	0	
0	0	0	0	0	0	0	0	0	0	0	0	0	0	
1	1	0	1	1	0	0	0	0	0	0	0	0	0	
0	1	0	0	1	0	0	0	0	0	0	0	0	0	
1	1	0	1	1	0	0	0	0	0	0	0	0	0	
0	1	0	0	1	0	0	0	0	0	0	0	0	0	
0	1	0	0	0	0	0	0	0	0	0	0	0	0	
0	1	0	0	0	0	0	0	0	0	0	0	0	0	
0	0	0	0	0	0	0	0	0	0	0	1	0	0	
0	0	0	0	0	0	0	0	0	0	0	1	0	0	
0	0	0	0	0	0	0	0	0	0	0	1	0	0	
0	0	0	0	0	0	0	0	0	0	0	1	0	0	
0	1	0	0	0	0	0	0	0	0	0	0	0	0	
0	0	0	0	0	0	0	0	0	0	0	0	0	0	
1	1	0	1	1	0	0	0	0	0	0	0	0	0	
0	0	0	0	0	0	0	0	0	0	0	1	0	0	
0	0	0	0	0	0	0	0	0	0	0	1	0	0	
1	0	0	1	0	0	0	0	0	1	1	0	0	0	
1	0	0	1	0	0	0	0	0	1	1	0	0	0	
0	0	0	0	0	0	0	0	0	0	0	0	0	0	
0	0	0	0	0	0	0	0	0	0	0	0	0	0	
0	0	0	0	0	0	0	0	0	0	0	0	0	0	
0	0	0	0	0	0	0	0	0	0	0	0	0	0	
0	0	0	0	0	0	0	0	0	0	0	0	0	0	

Figure B2-16 Variables for Criticality Model in ArcGIS Attribute Table



Table

Criticality - Model

	TARGET_Criticality_Score_Level	Criticality_Level	TARGET_Criticality_Level	Criticality_Model_Pred	PAN	TARGET_PAN	M
	Very Low	2	1	1	590	579	REF
	Moderately Low	4	2	2	600	689.6	REF
	Very Low	2	1	2	360	485.6	REL
	Very Low	4	1	4	640	555.6	REF
	Very Low	2	1	2	360	485.6	REL
	Moderately Low	4	2	2	450	539.6	REL
	Very Low	2	1	2	470	477.4	REL
	Moderately Low	5	2	2	700	609.6	UP
	Moderately Low	5	2	2	700	689.6	UP
	Very Low	2	1	2	360	485.6	REL
	Moderately Low	5	2	2	700	689.6	UP
	Moderately Low	5	2	2	700	689.6	UP
	Moderately Low	5	2	2	700	609.6	UP
	Moderately Low	5	2	2	700	609.6	UP
	Very Low	2	1	2	550	568.2	REL
	Moderately Low	4	2	4	450	541.4	REL
	Moderately Low	4	2	2	450	539.6	REL
	Medium	5	3	5	700	631.2	UP
	Moderately Low	3	2	2	390	509	REL
	Moderately Low	5	2	2	700	609.6	UP
	Very Low	2	1	2	510	635.6	REL
	Very Low	2	1	2	590	568.2	REF
	Very Low	2	1	2	550	608.2	REL
	Moderately Low	4	2	2	490	461.4	REL
	Moderately Low	4	2	4	450	581.4	REL
	Moderately Low	3	2	2	350	349	REL
	Very Low	2	1	2	360	485.6	REL
	Very Low	2	1	2	510	637.4	REL
	Very Low	2	1	2	360	485.6	REL

0 (0 out of 24082 Selected)

Criticality - Model

Figure B2-17 Criticality Values in ArcGIS Attribute Table

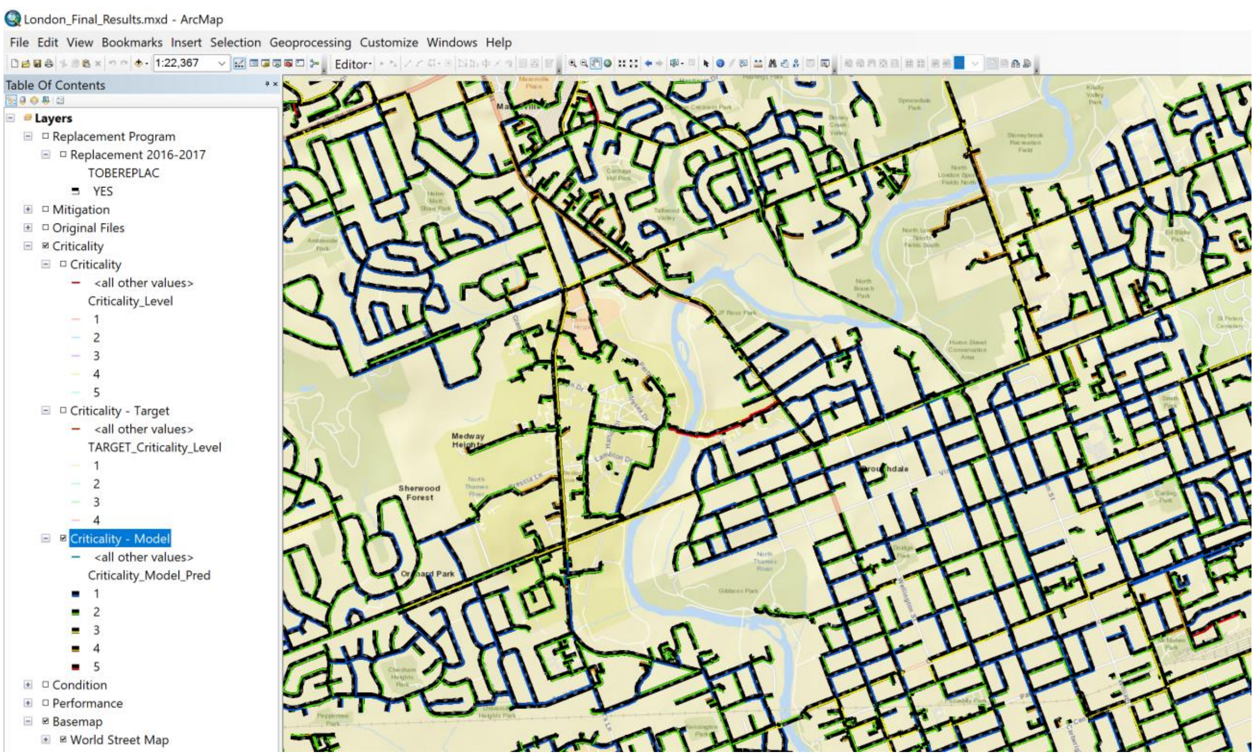


Figure B2-18 Criticality Model Results in ArcGIS

Table

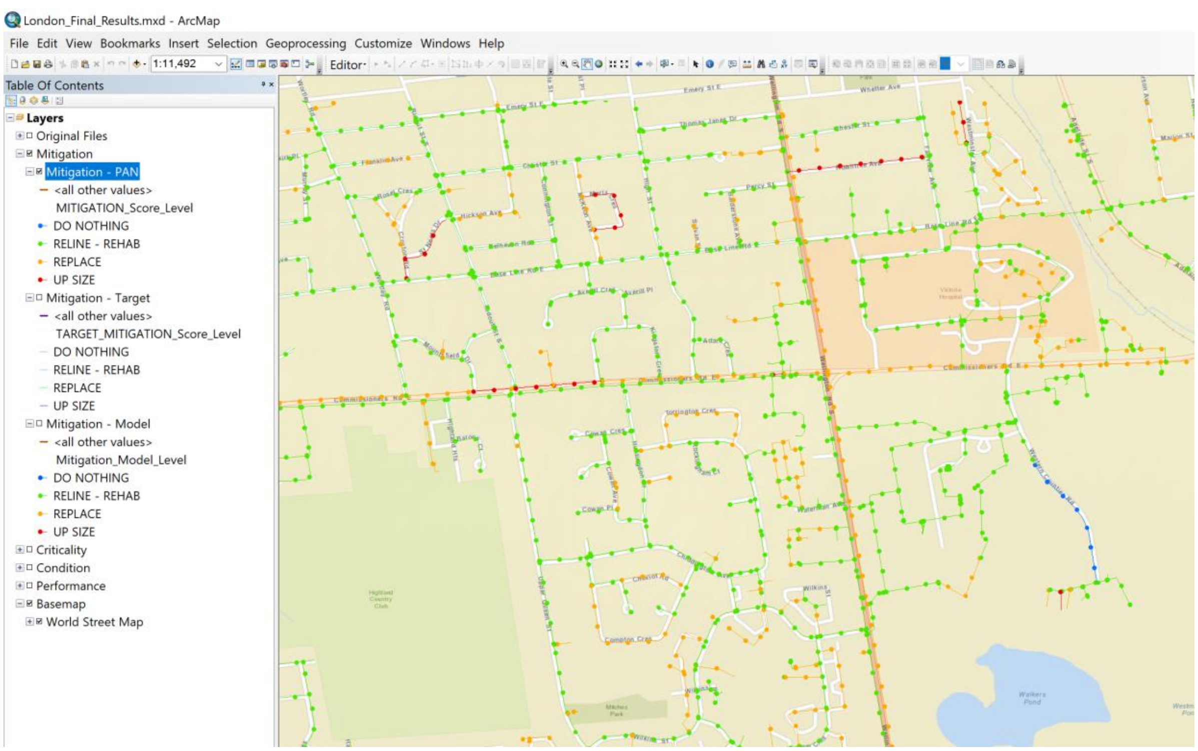
Mitigation - Model

PAN	TARGET_PAN	MITIGATION_Score_Level	TARGET_MITIGATION_Score_Level	MITIGATION_Level_PAN	TARGET_MITIGATION_Level_PAN	Mitigation_Model_Pred	Mitigation_Model_Level
590	579	REPLACE	REPLACE	3	3	3	REPLACE
600	689.6	REPLACE	REPLACE	3	3	3	REPLACE
360	485.6	RELINE - REHAB	RELINE - REHAB	2	2	2	RELINE - REHAB
640	555.6	REPLACE	REPLACE	3	3	3	REPLACE
360	485.6	RELINE - REHAB	RELINE - REHAB	2	2	2	RELINE - REHAB
450	539.6	RELINE - REHAB	RELINE - REHAB	2	2	2	RELINE - REHAB
470	477.4	RELINE - REHAB	RELINE - REHAB	2	2	2	RELINE - REHAB
700	609.6	UP SIZE	UP SIZE	4	4	4	UP SIZE
700	689.6	UP SIZE	UP SIZE	4	4	3	REPLACE
360	485.6	RELINE - REHAB	RELINE - REHAB	2	2	2	RELINE - REHAB
700	689.6	UP SIZE	UP SIZE	4	4	3	REPLACE
700	689.6	UP SIZE	UP SIZE	4	4	3	REPLACE
700	609.6	UP SIZE	UP SIZE	4	4	4	UP SIZE
700	609.6	UP SIZE	UP SIZE	4	4	4	UP SIZE
550	568.2	RELINE - REHAB	RELINE - REHAB	2	2	2	RELINE - REHAB
450	541.4	RELINE - REHAB	RELINE - REHAB	2	2	2	RELINE - REHAB
450	539.6	RELINE - REHAB	RELINE - REHAB	2	2	2	RELINE - REHAB
700	631.2	UP SIZE	UP SIZE	4	4	4	UP SIZE
390	509	RELINE - REHAB	RELINE - REHAB	2	2	2	RELINE - REHAB
700	609.6	UP SIZE	UP SIZE	4	4	4	UP SIZE
510	635.6	RELINE - REHAB	RELINE - REHAB	2	2	2	RELINE - REHAB
590	568.2	REPLACE	REPLACE	3	3	4	UP SIZE
550	608.2	RELINE - REHAB	RELINE - REHAB	2	2	2	RELINE - REHAB
490	461.4	RELINE - REHAB	RELINE - REHAB	2	2	2	RELINE - REHAB
450	581.4	RELINE - REHAB	RELINE - REHAB	2	2	2	RELINE - REHAB
350	349	RELINE - REHAB	DO NOTHING	2	1	1	DO NOTHING
360	485.6	RELINE - REHAB	RELINE - REHAB	2	2	2	RELINE - REHAB
510	637.4	RELINE - REHAB	RELINE - REHAB	2	2	2	RELINE - REHAB
360	485.6	RELINE - REHAB	RELINE - REHAB	2	2	2	RELINE - REHAB

0 (0 out of 24082 Selected)

Mitigation - Model

Figure B2-19 PAN and Mitigation Values



FigureB2-20 PAN Result in ArcGIS

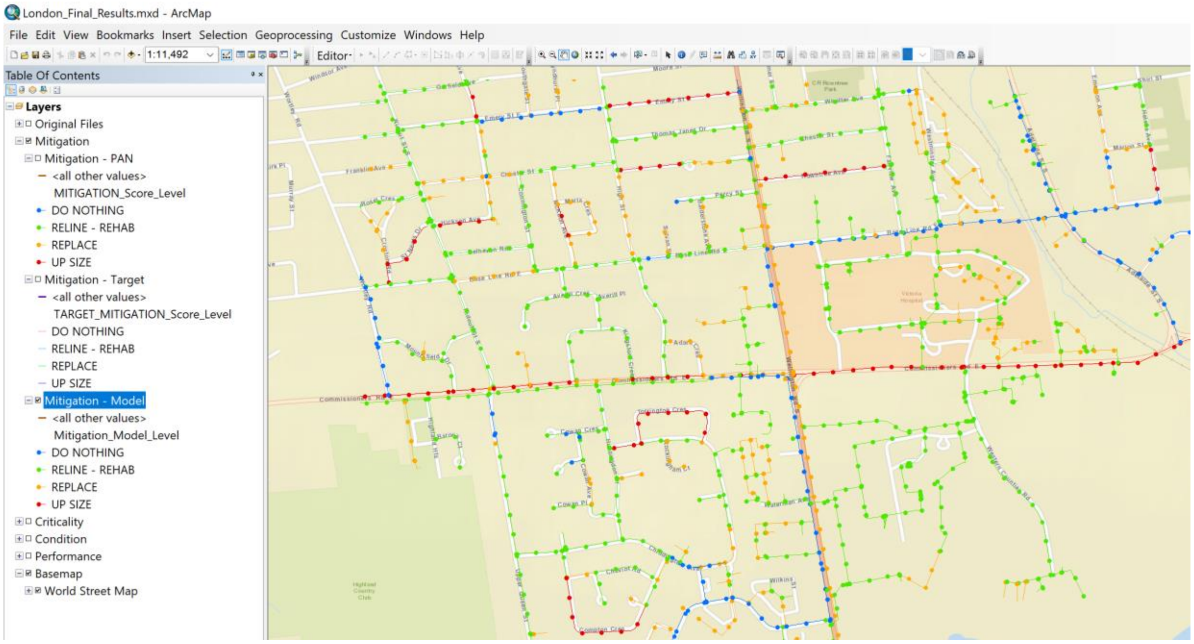


Figure B2-21 Mitigation model Results in ArcGIS

B 3 Appendix B3 - The City of London Water Network Data

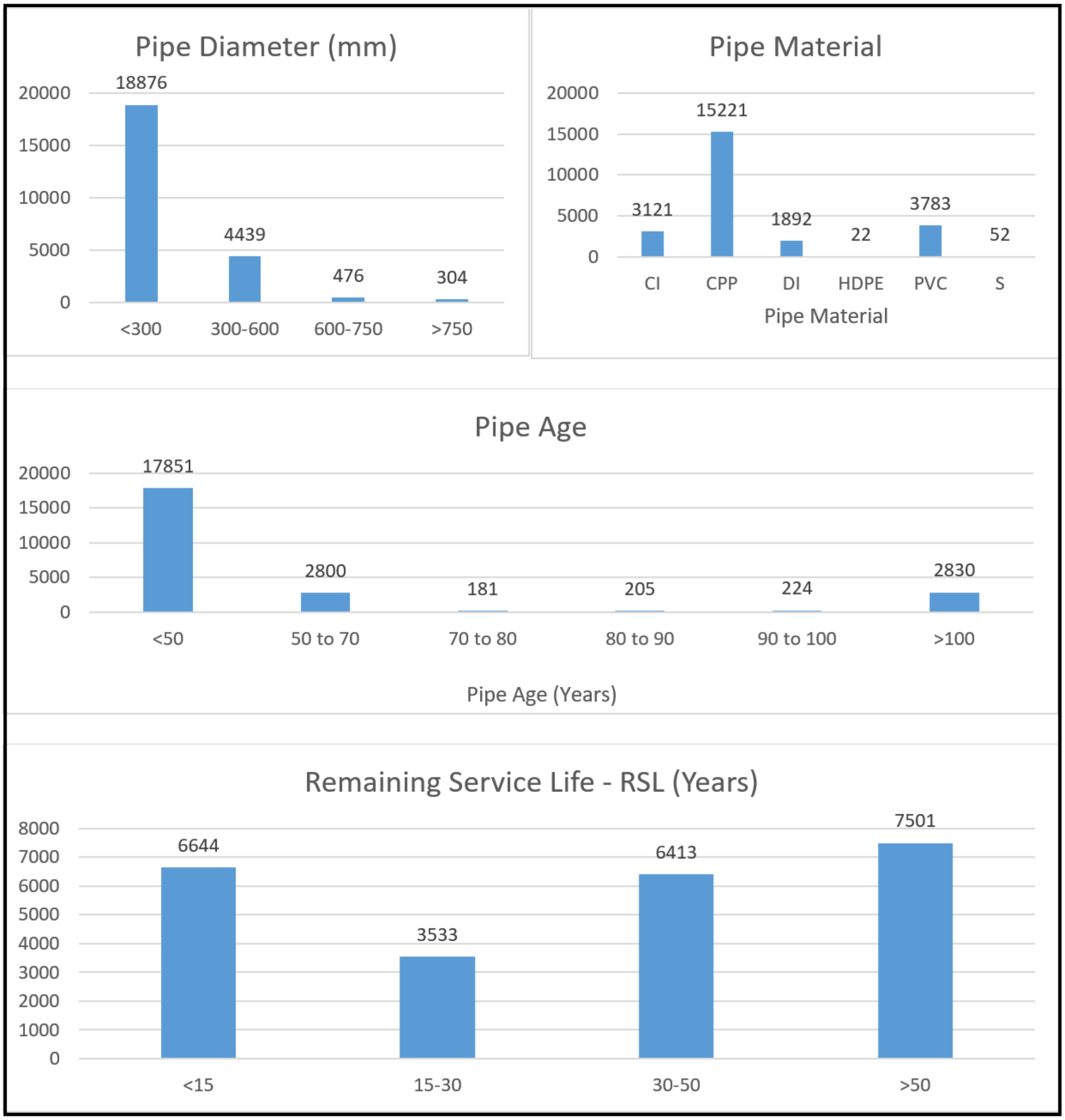


Figure B3-1 City of London Pipe Information Histograms

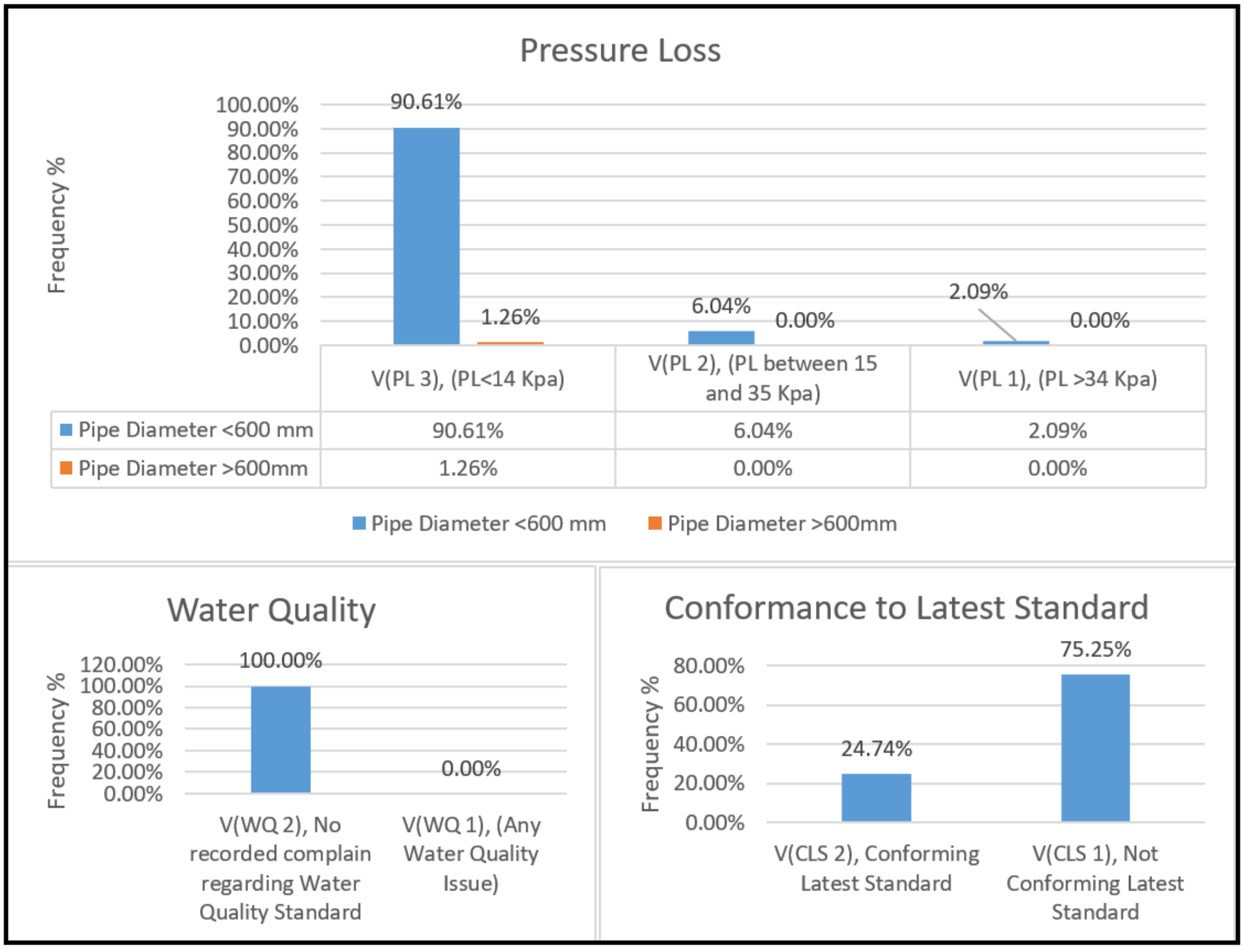


Figure B3-2 City of London Performance Attributes Histograms

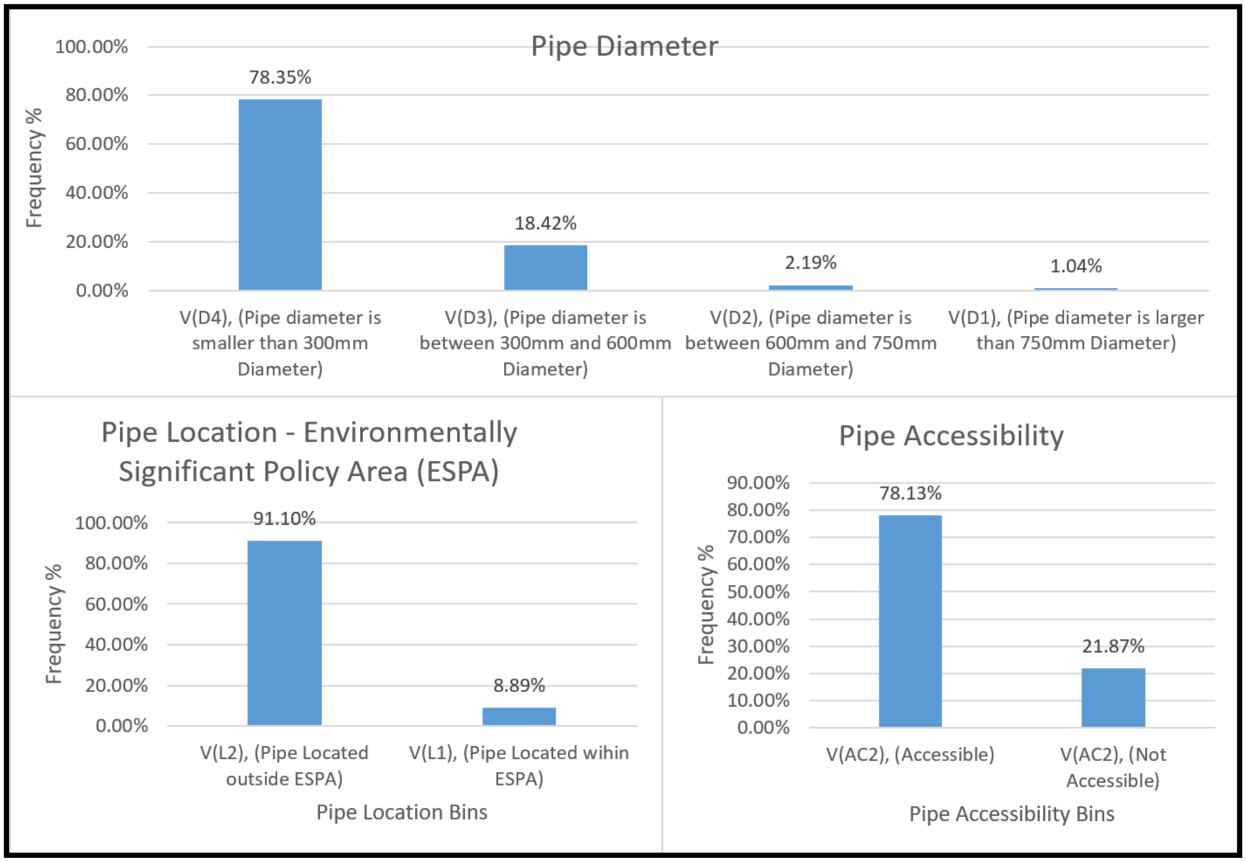


Figure B3-3 City of London Criticality Attributes Histograms