SENSITIVITY ANALYSES AND META-MODELING IN COMPLEX DECISION SUPPORT TOOLS FOR TRANSPORTATION ASSET MANAGEMENT

by

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A dissertation submitted to the Faculty of the University of Delaware in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Civil, Construction, and Environmental Engineering

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABSTRACT

The importance of decision support tools in transportation asset management (TAM) cannot be over-emphasized. Decision support tools have been developed to solve a variety of TAM problems, yet Departments of Transportation (DOTs) also continue to develop new decision support models without necessarily measuring the perceived benefits from the new model viz-a-viz existing models. Furthermore, some studies, as well as interactions with practitioners, have shown that the agencies sometimes revert to simple, legacy tools due to the blackbox nature of newer, more complex models, as well as their analytical and computational requirements. Efforts should be made to encourage appropriate use of the available complex tools.

This research involved two objectives. The first objective explored the role of verification and validation of decision models in TAM through variance-based sensitivity analysis techniques. The sensitivity analysis helps to understand how model parameters and variables influence policies and decision, thereby reducing the skepticism inherent in the use of complex models. The second objective proposed and implemented a meta-model framework as a higher-level tool to facilitate the matching of a set of decision support tools to appropriate decision contexts.

In the first objective, a global sensitivity analysis technique, called Sobol's method is used to identify the importance of the model's input variables and

parameters of a case-study complex decision support tool. The analysis showed that, unlike local methods, where the sensitivity of the model's outcomes to the inputs are examined one at a time, the Sobol method showed a superior ability to identify the interactions among parameters and their importance. That is, the analysis showed that one must be careful in dealing with the parameters in complex decision support tools as there is a tendency to erroneously underestimate the influence of some parameters on the output when they are considered independently as opposed to their combined effects which may reveal that they are otherwise consequential to the outcome of the model.

In the second objective, a machine-learning-based meta-model procedure for selecting appropriate support tools for specific decisions according to the scenarios encountered was demonstrated. Three case study decision support tools were applied to different decision scenarios that are characterized by the transportation network variables. A model assignment rule for selecting the most appropriate tool for each scenario was defined using the differences in the outputs from the different tools. This produced a labeled dataset for each decision scenario. A chi-square test performed on this data revealed a significant association between the congestion levels on the networks and the choice of decision thereby reinforcing a hypothesis that the complex tool may be favored in congested networks. A cluster analysis indicated that two of the three models were dominantly favored in all the clusters identified, suggesting that the asset manager may focus less on the third model. The labels of the scenarios were reassigned disregarding the least dominant model and a classification model was trained to predict the appropriate tool to use for future scenarios. Five classification algorithms, logistic regression, support

vector machine, k nearest neighbor, decision trees and random forest, were trained. Principal component analysis was to reduce the dimensionality of the data and the principal components were used as the independent variables. The findings show that it is possible to reduce the catalog of decision support tools available to solve the same problem by identifying the ones that will not apply to a group of scenarios with similar characteristics. The performance of the meta-model classifier also shows that the proposed framework can predict the most preferred decision support tools to use for previously unseen scenarios.

In summary, complex decision support tools have their place in TAM. However, their use is not always warranted. Furthermore, users of such models should conduct rigorous local and global sensitivity analysis to verify that the models behave as expected and to assist in parameter selection. This research demonstrated the value of such rigorous sensitivity analysis and the meta-model framework in the context of three decision tools and a selection of toy networks. Additional research is needed to determine whether these conclusions apply to other decision-support tools and larger networks.

Chapter 1

INTRODUCTION

1.1 Background

Transportation infrastructure constitutes one of the critical infrastructures in any nation as it provides a platform upon which economic and other societal activities are built. Although this infrastructure is built to last decades, frequent use and exposure to routine and extreme environmental conditions cause it to deteriorate over time, necessitating routine maintenance and rehabilitation to prolong its life. Scheduling and prioritizing these maintenance and rehabilitation activities are not easy for asset managers due to limited resources and the many, often conflicting, options available.

Aging infrastructure, increasing traffic demand, limited infrastructure funding, and continuously changing performance requirements are some of the challenges to infrastructure management. The fact that individual asset classes, like bridges and pavements, present distinct asset management challenges also adds to the complexity. As a result, infrastructure managers often rely on several modeling and decision-support tools. These tools are mostly built upon optimization techniques to prioritize among multiple decision scenarios. However, most of these models are developed to solve specific problems with different input factors and usually on small networks with little chance of generalizing over more complex networks and management scenarios. In addition, the disparities in the practices

adopted by different transportation agencies have also contributed to the widespread and somewhat inconsistent adoption of asset management principles by highway agencies. In fact, it is feared that despite the potential opportunities realized from the use of these models, there exists skepticism among transportation agencies due to obscurities in the application of more complex models (Z. Wang & Pyle, 2019).

Hitherto, there has been little to no effort made to identify and synthesize the attributes of the various problems and models. Such endeavor aims to create a comprehensive toolbox that identifies when complex models are needed or simple models are adequate and is accessible to asset managers and the research community. Chen and Bai (2019) after reviewing over 337 articles on the application of optimization to infrastructure management asserted that although most of the algorithms encountered were different, the problems explored were mostly similar. However, there is no attempt to define which model is best, or most appropriate, or to integrate the models. It was highlighted that, while the numerous articles on asset management optimization methods in literature have demonstrated great results, the models mostly present a customized approach (i.e., usually one method is discussed) to solving a specific problem, thus making it difficult to have a comprehensive knowledge of the broad application of optimization methods in transportation asset management (TAM). Chen and Bai also deduced that although optimization can be conducted at the project or network level, network-level optimization has garnered traction among researchers of late.

Decision support tools for transportation asset management present challenges that inhibit their widespread adoption. For instance, the models are

usually developed to solve a unique problem encountered by highway agencies. Generalizing the decision support models is difficult, selecting the right tool and the appropriate model parameters for any application is complicated, validation of model results is near impossible, and there is an inherent fear of "black boxes".

Furthermore, there is also the issue of the models being adapted during the development stages to a simple case study that is sometimes impractical, thus making it difficult to apply the models to more complex scenarios. This, for instance, is often the case when toy highway networks are used to demonstrate proof of concepts, and the concept fails to generalize over complex networks. Also, there is an issue of inexplicability in some models i.e., uncertainty in the parameters, obscurities in the modeling process, and difficulty in the interpretation of results. For complex models which are usually built upon optimization techniques, a set of random decision variables are required as inputs to the models to obtain decision outcomes. Because these complex functions are usually a black box of mathematical expressions, there is a need to understand the impacts of each of the input variables and identify the ones that least significantly impact the output such that can be obviated during preliminary investigations (Alhossen, Baudoin, Bugarin, Segonds, & Teyssèdre, 2019).

The impacts of these challenges can vary depending on the complexity of the decision model in question. More complex models attempt to account for interactions among components, and impacts to different stakeholders, for example, disruptions to users due to maintenance activities. As the complexity of the model increases from simple rule-based tools to complex blackbox models, the

inexplicability of model behaviors, as well as the analytical requirements (time and computing requirements), also increases.

Figure 1.1 illustrates this phenomenon. Given the limited time available for infrastructure managers to select an action (a decision) from multiple options, they may be confronted with tradeoffs among precision, accuracy, consistency, computational efficiency, and data requirements in the decision-making process. Recognizing these challenges during the model development phase, particularly for complex models, can help reconcile the tradeoffs. For example, guidelines can assist decision-makers in determining when the simple models are sufficient to obtain desired outcomes without having to worry about the opportunity cost of running the complex models.

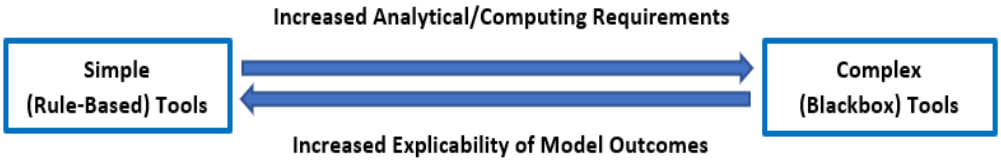


Figure 1.1: Explicability and analytical requirement in decision support tools.

In this research, the role of verification and validation of decision models in Infrastructure Asset Management is first demonstrated through variance-based sensitivity analysis techniques to understand more about their model variables thereby reducing the skepticism inherent in the use of complex models. Then, a meta-model framework is proposed as a higher-level tool that facilitates the

matching of a set of decision support tools to appropriate decision contexts i.e. a higher-level tool that suggests the most preferred option from a pool of options that solves the same problem. The remaining sections of this chapter present the motivation for this research, the problem statement, research objectives and scope, contributions, an outline of the dissertation proposal, and the anticipated research contributions.

1.2 Motivation

The idea of simplifying infrastructure management tools stems from the need to maximize information from, and experience using the models developed as part of two research projects funded through the Center for Integrated Asset Management for Multimodal Transportation Infrastructure Systems (CIAMTIS). These projects provide examples of complex tools applied to a toy problem to demonstrate a proof of concept. Each model is briefly described below.

The first model is a tool for toll pricing discovery, which is intended to help state departments of transportation (DOTs) plan toll suspension and form compensation strategies with toll concessionaires to ease traffic disruption during unanticipated construction where partial or full road closure is implemented. The model is a bi-level optimization framework in which the upper- and lower-level optimizations seek to also solve different bilevel optimizations, thus resulting in a four-level optimization problem. Using this model, toll prices can be set at a reduced rate to encourage road users to use tolls adjacent to roads undergoing improvement thus reducing the social costs, and DOTs compensate the concessionaires (Mamdoohi & Miller-Hooks, 2022).

The second model, which is the focus of this research, is a reinforcement learning-based bi-level optimization model for strategic prioritization and scheduling of infrastructure asset maintenance. This model considers traffic capacity loss during improvement action execution, traffic impacts of improved serviceability after the actions are complete, and uncertain deterioration mechanisms jointly across multiple asset classes, namely bridges and pavements, and suggests cost-effective improvement decisions over a stipulated improvement planning horizon (W. Zhou, Miller-Hooks, Papakonstantinou, Stoffels, & McNeil, 2022).

Although both models show significant benefits over naïve or simple solutions, they are complex, computationally intensive and have only been applied to modest networks, thus making it difficult to easily adapt to other scenarios without directly involving the original developer. This experience confirms the skepticism of using complex models by highway agencies as highlighted in (Z. Wang & Pyle, 2019). Since highway practitioners may need to make quick decisions about infrastructure management and may not always be able to contract this task to consultants regularly especially if the model must always be customized for different scenarios spanning across numerous facilities, it is not efficient that the model can only be modified by the originators. Instead, effort should be made to reduce the skepticism of the users of the models.

1.3 Problem Statement

A literature search reveals that many problem-solving techniques, and decision models, have been developed to solve similar TAM problems (Atolagbe

& McNeil, 2023c). Some DOTs, also continue to develop new decision support models without necessarily measuring the perceived benefits from the new model viz-a-viz existing models. In fact, interactions with practitioners have shown that they sometimes revert to simple, legacy models due to the blackbox nature of newer, more complex models. Given a pool of available model options, deciding which to use in different scenarios can be overwhelming to asset managers who are the actual users of the models – a situation that often favors the simple models that may not be optimized for the given scenario. Also, since these tools often have inherent complexities due to uncertainties in, and interactions among, the parameters and variables that influence the decision outcomes, understanding the behaviors of these parameters and/or variables, may help reduce the complexities in the components of the models, and the models at large.

1.4 Research Objectives

This research aims to explore methods that can facilitate improved explicability of decision model outcomes, reduce their complexities, and inspire generalizability of the models for real-life applications. This is achieved through the following objectives:

- Demonstrate the use of variance-based sensitivity analysis technique for identifying less consequential input variables and parameters of decision tools thus improving model fidelity.
- Propose and demonstrate a meta-model procedure for selecting appropriate support tools for decisions according to the scenarios encountered using applicable machine learning techniques.

1.5 Research Scope and Overview of Methodology

The applications of decision support tools cover the diverse classes of infrastructure including but not limited to highways, water resources, and the power grid. In this research, the focus is on decision-making in transportation systems, and in particular, the scope is limited to decision tools for highway assets. While there are several such tools in the literature for TAM applications (Atolagbe & McNeil, 2023c), this research focuses on the TAM problem for which W. Zhou et al. (2022)'s decision model solves a multi-class asset maintenance prioritization and scheduling considering traffic impacts problem to determine an optimal maintenance policy for roads and bridges based on condition thresholds.

To address the overall objective to facilitate improved explicability of decision model outcomes, reduce their complexities, and inspire generalizability of the models for real-life applications, this research addresses the two objectives presented in Section 1.4. in two parts. Each part uses a different methodology but the same case study and decision support tools.

The first part explores methods to connect model inputs and parameters to model outputs using a rigorous local and global sensitivity analysis. While local sensitivity analysis is widely used, global sensitivity analysis is less used in the transportation community. These methods can be used to validate and evaluate alternative tools and identify areas for improvement.

The second part develops a machine-learning-based meta-model procedure for selecting appropriate support tools for specific decisions according to the scenarios encountered. This also involves developing a strategy to characterize scenarios. This part relies on measures of network topology and congestion to

characterize scenarios, cluster analysis to group scenarios, principal component analysis to reduce the number of variables, and machine learning classification algorithms (logistic regression, support vector machine, k nearest neighbor, decision trees and random forest) to select the appropriate decision support tools for new scenarios.

Descriptions, in the context of this work, of terms used throughout this dissertation are summarized in Table 1.1.

Table 1.1: Definition of relevant terminology

Terminology	Description	Source
Blackbox	Tools for which only the inputs and outputs are known to the user. How the outputs are obtained is unknown.	Atolagbe and McNeil, 2023c
Complexity	Computational effort required to determine the maintenance policy. The computational effort (and complexity) increases as models include more parameters and interactions.	Atolagbe and McNeil, 2023c
Decision support/ Decision support tools	Tools that are used by transportation agencies to determine which action (maintenance, rehabilitation, or reconstruction) is applied to each facility in a transportation network and when.	Atolagbe and McNeil, 2023c
Machine learning	Science of discovering and analyzing useful patterns and structures from data to facilitate decision making	Attoh-Okine, 2017
Network Analysis	Group of techniques that uses the principles of graph theory to study the interactions among entities such as persons, organizations, physical objects, and systems	Taylor, 2017
Transportation Asset Management (TAM)	Transportation Asset Management is a strategic and systematic process of operating, maintaining, upgrading, and expanding physical assets effectively throughout their lifecycle. It focuses on business and engineering practices for resource allocation and utilization, with the objective of better decision making based upon quality information and well-defined objectives	FHWA, 2025

1.6 Dissertation Structure

This dissertation is divided into seven chapters. This chapter, Chapter 1, describes the attributes of decision support tools found in transportation infrastructure asset management, their applications, and the challenges encountered with their usage. Research objectives, motivation, scope, and research contributions are also presented in this chapter. Chapter 2 reviews decision support tools in transportation asset management. Chapter 3 presents a discussion of the case-study infrastructure asset management problem, as well as the development of decision support tools applicable to this research. Chapter 4 presents a discussion on what local and global sensitivity analyses tell agencies about asset management decision support tools. Chapter 5 presents a brief discussion on meta-models, machine learning, and network analysis, three concepts that are relevant to the development of the proposed meta-model framework for matching decision tools to decision scenarios. Chapter 6 presents a detailed discussion on the development and evaluation of the proposed framework. Chapter 7 presents conclusions, recommendations, and future work.

Chapter 4 is structured as a stand-alone research paper and includes a review of the relevant literature and a description of the methodology used for the sensitivity analysis. Likewise, the contents from Chapters 5 and 6 make up another stand-alone research paper.

Three appendices document supplementary material. Appendix A documents the networks and their characteristics that are used to develop the meta-models. Appendix B includes supplementary figures for the exploratory data

analysis for the dataset generated to develop the network models. Appendix C provides the application of the metamodel framework on an example network in Newark, Delaware with realistic data.

1.7 Research Contributions

So far, the challenges that come with the applicability of decision models for infrastructure systems analysis have been highlighted. There is yet no existing attempt to categorize or synthesize the decision support models in such a way that asset managers, who often have to make multiple decisions within the short time frames, can truly leverage the catalog of available decision tools to quickly determine the appropriate tool to use for a specific scenario. This research provides that opportunity. Using the framework presented in this research, decision-makers can quickly decide on when to use simple models versus complex models thus eliminating the need to wait on decision outcomes from time-consuming blackbox models when they may eventually be unwarranted.

This research also supports the objectives of the Federal Highway Administration's (FHWA's) recent initiative "Analysis, Modeling and Simulation" (FHWA, 2023a) to make decision systems more useful, as well as standardize simulation efforts for transportation systems. While the FHWA initiative is focused on connected automation and congestion management/mitigation, the concerns with the array of possible tools, the opportunities to leverage emerging technologies and the need to make efficient investments are common to transportation asset management. This work serves as a first-of-its-kind in transportation asset management.

Contributions to the research community through conferences and journals are as follows.

- A conference paper (Atolagbe & McNeil, 2023a) covering the background material, which was extended to a journal article (Atolagbe & McNeil, 2023c). Another conference paper (Atolagbe & McNeil, 2023b) focusing on sensitivity analysis, which was extended to a journal paper (Atolagbe & McNeil, 2024b) that is currently under review for the Transportation Research Record. A third journal paper exclusively focused on the proposed meta-model framework is also anticipated for submission to the Journal of Infrastructure Asset Management.
- The work on network properties and the initial meta-model framework was presented at the following conferences:
    - American Society of Civil Engineers (ASCE) International Conference on Transportation and Development (ICTD), Austin, Texas in June 2023,
    - Transportation Asset and Infrastructure Management (TAIM) Conference, Lancaster in October 2023,
    - SIAM5 (Symposium on Infrastructure Asset Management) held in Sydney, Australia in March 2024,
    - VISIM (Virtual Interuniversity Symposium on Infrastructure Management) in May 2024 and
    - AISIM (Annual Interuniversity Symposium on Infrastructure Management) held in Boulder, Colorado in May 2024.

Chapter 2

DECISION SUPPORT TOOLS IN TRANSPORTATION ASSET MANAGEMENT

2.1 Introduction

Although the annual budgets for highway infrastructure continue to grow, aging infrastructure, as well as increasing number of assets to support development present infrastructure owners with maintenance, rehabilitation and improvement needs that exceed budgets. These constraints restrict the scope of the maintenance and rehabilitation activities that can be implemented at any given time. At the same time, there continues to be increased pressure on the decision-makers to maintain high standards of infrastructure reliability and safety while meeting the expectations of the users regarding the efficiency of the infrastructure systems (Schraven, Hartmann, & Dewulf, 2011). Providing solutions to these challenges is at the core of TAM (Schraven et al., 2011). Realizing this goal requires decision support tools that effectively model the systems for which optimal decisions are being sought. This chapter describes the attributes of decision support tools found in transportation TAM, their applications, and the challenges encountered with their usage.

2.2 Decision Levels in Transportation Asset Management (TAM)

The types of decision-making in TAM can be classified into three hierarchical levels. These are: strategic level, network or program level, and project level (Haas, Hudson, & Zaniewski, 1994). Identifying the level that a decision scenario falls into depends on factors such as the decision objectives i.e., technical, administrative, or political, and the data (i.e., level of detail) required for such decision. Each level is associated with a type of decision: the project level is associated with decisions about a particular infrastructure component, such as when to resurface a specific bridge deck, the network or program level is associated with decisions across a network, such as the condition threshold at which bridge decks are replaced; and the strategic level is associated with system-wide decisions, such as the allocation of budgets between bridges and pavements. Figure 2.1 depicts the levels of decision-making in TAM.

2.2.1 Project Level

Project level decisions are those associated with individual projects at any given instance. At this level, the decision-makers utilize an approach tailored to the specific asset wherein only one project is planned for, and all the information and discussions revolve solely around that project. For example, a single bridge or pavement can be planned for maintenance and rehabilitation in isolation by gathering information about the needs for implementing the project. Such needs may be the current performance, types of repair strategy and design, scope of work, cost and benefit etc. Typically, the decisions at this level are very technical compared with those at the other two levels. Likewise, the data needs at this level

usually involve high levels of detail, focusing, again, solely on that project (Haas et al., 1994).

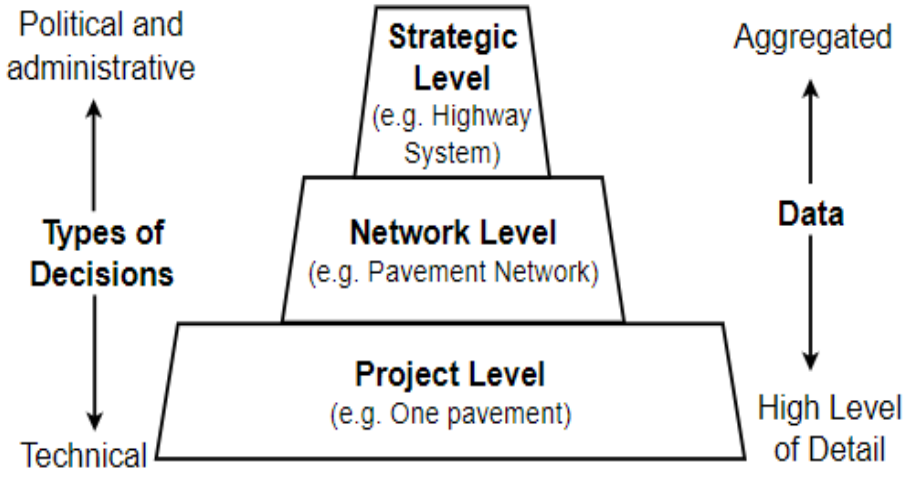


Figure 2.1: Levels of decision-making in transportation asset management - adapted from (Haas et al., 1994)

2.2.2 Network Level

At network level decision-making, decision-makers consider a network of assets e.g., network of bridges or highways, with the objective to make decisions that optimize the performance of such network. This level of decision-making is used to make investment decisions and allocate resources to a group of projects or assets within the confines of available budgets. They are also used for long-range planning purposes. Typically, after the projects or assets in the network have been evaluated at the project level for best outcomes, the information about each project is used to make network or program-level decisions, but only as an aggregate such as the cost or benefit of the project. Technical information about each asset such as

repair strategy or alternatives is usually not required here. Although some technical decisions may be required, the levels of technicality are often lesser than those at the project level.

2.2.3 Strategic level

At the strategic level, decision-makers seek to enhance the infrastructure systems performance at large. The infrastructure systems, in the case of the transportation, can be a network of different asset classes such as bridges, highways, streets. Decisions at this level are based on the overall performance of the infrastructure system as well as a general overview of the different networks within the system and observed patterns of usage or degradation common to different networks that help plan for improved performance of the networks. Decisions made here are usually more administration-oriented or sometimes politically motivated as they may be tied to the strategic goals of the agency or the state. Such a strategic goal may be to prioritize safety which is one of the major concerns for strategic decision-making (Dehghani, Giustozzi, Flintsch, & Crispino, 2013). Other examples of such decisions can be to foster equitable distribution of transportation access or to prioritize customer welfare.

2.3 Decision Support Tools in TAM

Over the years, decision support tools, range from simple rule-based ranking methods to complex mathematical models, incorporating optimization techniques. These optimization techniques are well-established in operations research where scientific and mathematical methods are used for decision analysis,

and have been applied to various infrastructure problems. Typically, the simple rule-based methods use a set of predefined rules (Wei & Tighe, 2004) to evaluate the options and rank them based on the priorities of the decision-maker. These methods usually tend to be subjective as they are developed based on expert experience. On the other hand, the complex models seek optimal strategy from an objective function of some decision variables over a set of constraints. Such models have proven to be relevant for solving the various complex challenges encountered in infrastructure management where maintenance and rehabilitation activities are strategically planned from a pool of choices with competing objectives limited by available resources within a specified planning horizon. Since the more complex models are built upon optimization techniques, optimization methods are increasingly becoming popular in infrastructure management.

2.3.1 Rule-based Tools

These are tools that are developed based on past knowledge of the asset managers and are based on "if-then" scenarios. Their designs involve first identifying all the likely scenarios and their corresponding outcomes, questions are posed about these outcomes, and a set of "if-then" rules for different scenarios are generated. These methods are well established in pavement management systems, for example, where performance indices of the pavements are used to establish thresholds for different treatment responses. They are also found in the form of decision trees, such as in Wei and Tighe (2004), and in transportation asset management plans of several departments of transportation in the United States. Although, the more complex models are becoming popular and continue to evolve

as different optimization methods are implemented, the simpler rule-based techniques are still applied in many scenarios, as they are clearly understood, and provide consistent decisions.

2.3.2 Optimization-based Tools

This set of decision support tools are based on optimization techniques which are mathematical representations of the objective being sought. Optimization frameworks come in different forms, however, in their generic form, mathematical expressions are used to describe the relationships between the variables which influence the decision outcomes. These expressions are solved by seeking one or more objectives, with constraints defined by the management requirements (Chen & Bai, 2019).

In infrastructure asset management, several kinds of optimization methods have been implemented in literature, each having different attributes and applications. Historically, the application of optimization methods as decision support tools for TAM dates back to the 1970s when researchers first used dynamic programming to determine the lowest investment required to maintain the condition of a road project over a 10-year period in Jamaica. Then in the 1980s, the Arizona Department of Transportation incorporated optimization into the agency's pavement management system, and later in the 1990s, TAM expanded beyond single-objective decision (Chen & Bai, 2019).

Today, applications of optimization methods seek solutions to different objectives in TAM. Solution methods are largely classified into two, namely: exact methods and heuristic methods (Lin, Tsai, & Yu, 2012). Optimization problems in

TAM can be characterized by the type of problem, more specifically, the decision variables.

2.3.2.1 Solution Methods

2.3.2.1.1 Exact Solution Methods

Exact solution methods, also referred to as deterministic optimization methods, use the analytical properties of a problem to obtain a series of points that converge to a global solution (Lin et al., 2012). These models can take the form of priority-based optimization where alternatives are selected by priority based on the extent to which they satisfy the criteria. They can also take the form of enumeration-based optimization where all available alternatives are enumerated and the "best" one is selected. Moreso, they can be based on transformation-based methods where multi-objective optimization is transformed to one or more single objective sub-problems where each sub-problems are solved individually to obtain one or more Pareto solutions. They may also take the form of numerical methods and algorithms such as dynamic programming, dual programming, and branch and bound methods. These methods are very common for decision-making in TAM because they yield robust, stable solutions and are not significantly influenced by the size of the problem and the restrictiveness of the constraints (Chen & Bai, 2019).

2.3.2.1.2 Heuristic Solution Methods

These methods are useful when the problems cannot be easily solved by deterministic methods and are usually explored as alternatives to deterministic optimization to minimize their inherent computational time, however, the solutions

obtained from them are not always guaranteed to be globally optimal (Lin et al., 2012). Although the methods are easy to understand, apply, and implement, the quality of their solutions may be unstable due to factors such as the size of the problem, the restrictiveness of the constraints, parameter calibration etc. Typically, trials are conducted to make sure that the calibration of the algorithm is good enough to yield a stable and good solution (Chen & Bai, 2019).

2.3.2.2 Types of Problems

Problems are classified as maintenance scheduling, alternative selection and prioritization, and performance maximization. These problems involving the selection of projects, the timing of projects and tradeoffs among different levels of investment at the same location. Problems can minimize costs (such as agency costs, agency plus user costs, or total social costs) subject to a minimum acceptable level of performance or maximize performance subject to budget constraints. Problems can also consider equity, environmental impacts, risk of failure, improved resilience, or safety. Fundamentally, the decisions are a time-space resource allocation problem.

2.3.3 Software Tools for TAM

There are several off-the-shelf software tools that are designed as decision-support tools in transportation asset management. These tools are made of one or a combination of decision frameworks depending on the application's needs. Examples of such tools are MODAT (AASHTO, n.d.), GENEPAV-HDM4 (Adey, Hajdin, & Brühwiler, 2004; Chen & Bai, 2019), OPTIPAV System (Chen & Bai,

2019; Fwa, Chan, & Tan, 1996) etc. The problem with these software tools is that they are often limited to the application for which they were designed.

2.4 Applications of Decision Support Tools

The various challenges – including many alternative management strategies to choose from (particularly when network-level decisions are sought or long-range planning is involved), limited resources, obscure relationships between multiple possible decision outcomes, competing objectives, and risks introduced due to uncertainties in long-term projections – that confront decision making in TAM have birthed many decision tools. These tools have varied requirements capturing their unique differences for the different applications such as maintenance scheduling, alternative selection and prioritization, and performance maximization.

One of the foremost decision tool applications in TAM is resource allocation. Here, the decision tools and frameworks are constructed to consider the variables that influence the impacts of the resource distribution across multiple assets within the confine of available budgets. Such techniques are referred to as multicriteria decision-making (Dowd, Franz, & Wasek, 2018). In their work on the development of a decision-making framework for maintenance and modernization (M&M) of transportation infrastructure, Dowd et al. (2018) developed a three-step decision framework to optimize infrastructure systems availability. The framework utilized a systems-thinking approach to identify the most important factors that influence consequential decisions, a complex network analysis to evaluate the criticality of each component in the system, and a Bayesian network learning to remove subjective judgment in the existing real-world data. Dehghani et al. (2013)

also developed a decision support model for cross-asset resource allocation to achieve optimum and sustainable systems performance.

Decision support tools have also been developed for estimating investment costs, including user and agency costs, for maintenance strategy. The user costs are costs incurred by road users which can be in the form of delays (i.e., longer travel time) and operational costs such cost of fuel, tolls, depreciation of vehicles etc. These costs are a crucial component for evaluating decision alternatives for maintenance of infrastructure assets. Agency costs on the other hand are direct maintenance costs incurred by the infrastructure owners such as cost of construction, asset acquisition etc. Meneses and Ferreira (2013) developed a multi-objective decision-aid tool for pavement maintenance programming considering agency's maintenance and user costs. The model utilizes a deterministic multi-objective single-linked optimization framework together with the AASHTO's deterministic pavement performance model to seek objectives such as minimization of agency costs, minimization of user costs, minimization of residual value of pavements etc.

Time is a really important element in infrastructure decision-making. Time is important because condition and performance change over time, and different types of costs (for example, planning, construction, maintenance, repair, rehabilitation, and reconstruction) are incurred at different times over the life cycle of an asset. Decision tools have been designed to select alternatives based on life cycle costs. Life-cycle cost analysis is an essential component of infrastructure management as it enables decision-makers to compare different design alternatives and preservation strategies and select plans that yield the best investment value

(Batouli, Mostafavi, & Chowdhury, 2022). It also affords decision-makers the opportunity to adequately identify and evaluate the environmental impact of infrastructure and its socioeconomic impacts throughout their lifetime (Alaloul, Altaf, Musarat, Faisal Javed, & Mosavi, 2021). A dynamic network-level Life-cycle cost analysis (DyNet-LCCA) tool has been proposed by researchers for life-cycle analysis in evolving infrastructure systems. The framework of the DyNet-LCCA is made of four major steps that captures the evolutionary costs in infrastructure systems and another two steps that minimize the impact of uncertainty in estimating infrastructure costs for long-term projections (Batouli et al., 2022). Meijer et al. (2021) also developed LCA-Pave - a tool to assess the environmental impacts of pavement material and design decisions. LCA-Pave is a spreadsheet tool populated with national data for conducting life-cycle analysis of pavement systems. A systematic review of decision support tools for life cycle cost assessment has also been conducted by (Alaloul et al., 2021).

Another important application of decision tools is scheduling of asset preservation and maintenance interventions. Infrastructure assets are always initially constructed to the highest standards feasible with the available resources, but with time, they begin to experience deterioration due to use and exposure to harsh environmental conditions. To maximize the life span of the assets, decision makers aim to accurately predict when to implement treatment interventions which is typically when the performance of the assets falls below certain pre-determined thresholds, and hence are constantly seeking appropriate decision tools and frameworks to aid proper timing of interventions. Several Departments of Transportation in the United States have incorporated decision trees and thresholds

into their pavement asset management systems that are used to determine when interventions are required for pavement infrastructure (California Department of Transportation, 2018; Delaware Department of Transportation, 2019; Georgia Department of Transportation, 2019; North Carolina Department of Transportation, 2019; Pennsylvania Department of Transportation, 2019). More complex models such as the optimization framework developed by (X. Zhang & Gao, 2012) to determine the optimal length of the maintenance period based on the proposed maintenance policy to minimize the system's lifecycle cost, as well as the reinforcement learning algorithm developed by Hooks et al. (2021) which uses Markov decision processes for strategic prioritization and planning of multi-asset transportation infrastructure maintenance and rehabilitation also exists for scheduling preservation.

2.5 Challenges with Decision Support Tools in TAM

The major challenge that limits the application of decision tools in TAM is complexity of the decision framework due to the complex nature of the infrastructure systems themselves. Dehghani et al. (2013) characterized an ideal infrastructure management system as one that, within a reasonable limited budget, can preserve all the network sections at a high level of service in such a way that the structural, functional, and safety conditions are adequate. As such, a decision support tool seeking an optimal strategy for asset management should maximize the performance of the assets over their lifecycle, minimize agency and user costs, and reduce environmental impact. Since these requirements are conflicting in nature, most decision frameworks are built upon the principles of multi-objective

optimization. Unfortunately, these models become complex to design and interpret as the requirements increase especially when the number of objectives exceed three (Chen & Bai, 2019).

Dowd et al. (2018) proposed a comprehensive multi-objective decision framework for asset management. As noted by the authors, a comprehensive multi-objective decision framework for TAM should satisfy four conditions: (1) all important factors that influence the decision must be considered, (2) the structure of the transportation infrastructure networks and the interdependencies between their components should be captured, (3) the model should generate unbiased outcomes and diminish the impact of inaccuracies due to subjective judgments, and (4) implementation of trade-off analysis should be feasible (Dowd et al., 2018). Sadly, as compelling as these are, many decision tools do not satisfy all four of these requirements.

The complexity of decision support tools can also be seen in the fact that most of the existing models for TAM are designed for short-term operational needs rather than for long-term purposes. Likewise, most models are often treated in silos by disregarding the interaction effects of interconnected infrastructure thus underestimating the outcomes of such models (Bhamidipati, 2015). As infrastructure management decisions are intended for long-range planning, models built for short-term needs and those that neglect the interdependencies in the network are often inappropriate for long-term planning scenarios.

Inexplicability of model outcomes has also been a challenge with most TAM decision support tools. Z. Wang and Pyle (2019) highlighted that although applications of different optimization techniques in infrastructure are rigorously

grounded in the literature as well as designed to meet the needs of infrastructure owners, there is a lack of confidence in the outcomes of the models amongst transportation agencies, especially for complex decision scenarios. This is because most of the models are "blackboxes" of complex mathematical or programming expressions that are difficult to understand by the agencies, the intended users for which the models are designed. Although some of these tools are encapsulated in ready-to-use formats such as computer software that can provide the user with an interface to relate to the program, interpreting the results can still be challenging.

Furthermore, the inexplicability of model outcomes could often be attributed to the uncertainties in the model parameters. According to W. Wang and Wu (2021), model uncertainties could have negative, positive, or negligible impacts on the model outcomes. This could impact the complexity of the models thus affecting the performance of the model. Since a lot of uncertainties are inherent in all aspects of transportation systems, the decision tools are laced with these uncertainties thus potentially compromising the fidelity or generalization of the models.

In addition to the uncertainty in model parameters, there are challenges due to changing infrastructure systems networks. Apart from the fact that the decision models are designed to seek different decision outcomes, there is also the concern that some models can only solve project-level problems while others solve network problems. In a state-of-the-art review on the application of optimization to decision-making in TAM, it was noted that a significant number of recent optimization-based decision tools are built for network-level decisions compared with project-level decisions (Chen & Bai, 2019). Furthermore, for network-based models, there is a

need to adequately model the problem to capture the structure of the infrastructure network. Given the complexity of the decision problems and the computational needs, most studies in the literature such as Mamdoohi and Miller-Hooks (2022) and W. Zhou et al. (2022) use a small-sized test network structure to demonstrate the concept in the studies. This makes it difficult to automatically generalize the models for different scenarios over different structure of the network.

Chapter 3

CASE STUDY TRANSPORTATION ASSET MANAGEMENT PROBLEM AND DECISION SUPPORT MODELS

3.1 Introduction

Planning and scheduling maintenance strategies for highway networks do not come easy for highway agencies since many, often conflicting, factors must be considered. One method that has helped is to perform a life-cycle cost assessment of the network and make projections on what year during the planning horizon when certain treatments will be performed as well as the associated cost. The life-cycle cost assessment involves the calculation of different cost components of keeping the network at desired states through its life cycle and making decisions based on the minimum cost. This means that the direct (agency) and indirect (user) costs associated with every conceivable alternative maintenance intervention on different segments of the network must be determined. Doing this analysis optimally on a network is computationally intensive and hard, and often, modeling tools based on optimization techniques are employed to solve the problem. In addition, the intervention strategies differ for different asset classes such as in bridges and pavements, adding another layer of complication to the computations. Numerous tools have been developed for solving these problems and the numbers continue to increase.

Considering a highway network of pavements and bridges, where each segment is characterized by its individual condition state, geometric properties, and traffic capacities, and assuming the total life cycle costs are to be computed for the network, based on the agency and user costs of implementing actions and the disruption costs from traffic delays due to the actions over a specified planning horizon, W. Zhou et al. (2022) proposed a bi-level optimization framework for scheduling maintenance and computing the costs while inherently defining a maintenance policy to do so. A maintenance policy is a set of condition state thresholds that determines the state at which certain treatment action is warranted. Details of the model are contained in W. Zhou et al. (2022), however, the model serves as the basis for the case-study models in this dissertation.

Three decision support tools that are based on condition thresholds for specific assets were developed similar to that developed by W. Zhou et al. (2022). The tools are: (1) Predefined thresholds-based tool (2) Optimal thresholds-based tool optimized for agency and user cost (3) Optimal thresholds-based tool optimized for total cost. Each tool builds on the previous tool adding levels of complexity, where the predefined thresholds-based tool is the least complex and the optimal thresholds-based tool optimized for total life-cycle cost is the most complex. The first tool computes the costs (agency, user, and disruption) over the planning horizon given a policy. The second tool evaluates all possible policies and selects the optimal policy based on the average minimum agency and user cost over the planning horizon. The third tool also evaluates all possible policies but selects the optimal policy based on the average minimum total cost over the planning horizon. The average is used as the degradation of the assets (pavement segments

and bridges) is represented as a Markovian deterioration process and simulations representing different conditions states over the planning horizon are required to capture the uncertainty.

3.2 Model Background

A discussion of the concepts related to the development of the models is presented in the following sections. As the tools are based on the example problem in W. Zhou et al. (2022), the notation from W. Zhou et al. (2022) is adopted here using the same logic for determining the optimal thresholds. The notation used for each model is shown in Table 3.2 and Table 3.3. The last column shows values used by W. Zhou et al. (2022) for the case study and also adopted here.

3.2.1 Condition Thresholds and Maintenance policy

The threshold specifies an action for every condition state. Here the index t for the time period is not included but the process is repeated for each year. Considering pavement segment k, given $|A_k|$ actions, $|A_k|$ -1 thresholds are required to specify an action for each possible condition state (s_k). That is, the thresholds can be specified as ($\zeta_1, \zeta_2 \ldots\ldots \zeta_{|Ak|-1}$). However, to be consistent with W. Zhou et al. (2022), we define $|A_k|$ thresholds ($\zeta_1, \zeta_2 \ldots\ldots \zeta_{|Ak|}$) and assume $\zeta_1 = S_1$. The actions are then selected as follows:

If $\zeta_{ak+1} < s_k \leq \zeta_{ak}$ then select a_k: $a_k = 1 \ldots. |A_k|-1$

Else if $s_k \leq \zeta_{|Ak|}$ the select $|A_k|$

For example, using the notation shown in Table 3.2, if the specified threshold for a pavement segment is (6, 4, 2), the maximum condition state, 6,

indicates excellent condition, then the threshold value at which the do-nothing action ceases to apply is condition state 4. That is, as soon as the condition state hits 4, minor repair is required. The minor repair option is applicable until the condition state hits 2 where a major repair or rehabilitation is required. Using this example,

$|A_k| = 3$

$\zeta_1 = 6$, $\zeta_2 = 4$, $\zeta_3 = 2$

Select a^1 if $s^k > \zeta_2$ (or $\zeta_2 < s^k \leq \zeta_1$)

Select a^2 if $\zeta_3 \leq s^k < \zeta_2$

Select a^3 if $s^k < \zeta_3$

These action choices are shown in Table 3.1. The same approach can be used for bridges. A pair of the threshold for pavement and bridges make up a maintenance policy for the network. All feasible policies are found in Table 3.4. The first triplet represents the thresholds for pavement segments and the second triplet the thresholds for bridges.

Table 3.1: Example actions selection based on states, and thresholds

Condition states	6	5	4	3	2	1
Thresholds	6		4		2	
Actions	1	1	2	2	3	3

Table 3.2: Notation used in W. Zhou et al. (2022)

Indices	Description	Default values
b	Number of bridges, b=1… B	Varies
I	Number of policies, i=1…I.	I=60, For predefined threshold tool, I = 1
k	Number of road segments, k=1…K	Varies
n	Number of iterations of the decision-making process with different realizations of condition	n=5000 *
t	Year in planning horizon, t = 1...T	T=20 *
Condition	**Description**	**Default values**
S_b	State space of condition of bridge b, $S_b = (S_1, \ldots . S_{\lvert Sb \rvert})$	S_b = (5,4,3,2,1) $\lvert S_b \rvert$=5
S_k	State space of condition of roadway segment k, $S_k = (S_1, \ldots . S_{\lvert Sk \rvert})$	S_k = (6,5,4,3,2,1) $\lvert S_k \rvert$ = 6
s_t	Set of condition states for each link and bridge at year t	
Actions	**Description**	**Default values**
A_b	Set of potential bridge improvement actions for bridges, $a_b \in A_b$;	A_b = (1,2,3) = (Do-nothing, minor repair, major repair)
A_k	Set of potential pavement improvement actions for pavements, $a_k \in A_k$;	A_k= (1,2,3) = (Do-nothing, minor repair, major repair)
a_t	Set of actions for each link and bridge at year t	

Thresholds	Description	Default values
$\{(\zeta_1, \zeta_2 \ldots\ldots \zeta_{\lvert Ak \rvert}), (\sigma_1, \sigma_2 \ldots\ldots \sigma_{\lvert Ab \rvert})\}$	Threshold settings for pavements and bridges as a function of their condition state.	
$(\sigma_1, \sigma_2 \ldots\ldots \sigma_{\lvert Ab \rvert})$	Set of threshold settings for bridges with $\sigma_{\lvert A_k \rvert} < \cdots < \sigma_2 \; and \; \sigma_1 \leq \lvert S^b \rvert$	
$(\zeta_1, \zeta_2 \ldots\ldots \zeta_{\lvert Ak \rvert})$	Set of thresholds settings for pavements with $\zeta_{\lvert A_k \rvert} < \cdots < \zeta_2 \;\; and \; \zeta_1 \leq \lvert S^k \rvert$	
Costs	Description	Default values
$c_1(\mathbf{a_t})$	Agency costs in year t for actions $\mathbf{a_t}$	
$c_2(\mathbf{s_t})$	User costs in year t based on condition states $\mathbf{s_t}$	
$c_3(\mathbf{a_t})$	Disruption cost in year t based on actions $\mathbf{a_t}$	
Parameters	Description	Default values
d	Deterioration rate	
u	User cost rate	
m	Maintenance cost rate	
γ	Discount factor	$\gamma = 0.95$ *
i	Discount rate	$\gamma = {}^{1}/_{(1+i)}$
ρ	Traffic factor	ρ=0.05 *
vot	Value of time	*vot* =$18.70 / person hour

* Default values are as listed, except as specifically stated to change in the later experiments.

Table 3.3: Additional data used in W. Zhou et al. (2022)

Category	Data	Default Values
Link performance variables	BPR parameters	a = 0.15 and b = 4
	Link capacities	Varies
	Effect of link actions on capacities	Pavement – minor and major repair– closes half of the lanes
		Bridge – minor and major repair – full closure
	Free-flow speed	55 mph (or 82.5 km/hr)
Traffic demand variables	Value of time	$18.7/ person hour
	Occupancy	1/67 persons/ vehicle
	Travel delay costs	$31.22 / vehicle hour (18.7*1.67)
	OD Demand	8000 vehicles *
	Duration of disruption	8 hours per day *

* Default values are as listed, except specifically stated in the experiments to change

Table 3.4: Set of possible policies

#	Policy	#	Policy	#	Policy	#	Policy
1	{(6, 5,4), (5,4,3)}	4	{(6, 5,4), (5,3,2)}	7	{(6, 5,3), (5,4,3)}	10	{(6, 5,3), (5,3,2)}
2	{(6, 5,4), (5,4,2)}	5	{(6, 5,4), (5,3,1)}	8	{(6, 5,3), (5,4,2)}	11	{(6, 5,3), (5,3,1)}
3	{(6, 5,4), (5,4,1)}	6	{(6, 5,4), (5,2,1)}	9	{(6, 5,3), (5,4,1)}	12	{(6, 5,3), (5,2,1)}
13	{(6, 5,2), (5,4,3)}	16	{(6, 5,2), (5,3,2)}	19	{(6, 5,1), (5,4,3)}	22	{(6, 5,1), (5,3,2)}
14	{(6, 5,2), (5,4,2)}	17	{(6, 5,2), (5,3,1)}	20	{(6, 5,1), (5,4,2)}	23	{(6, 5,1), (5,3,1)}
15	{(6, 5,2), (5,4,1)}	18	{(6, 5,2), (5,2,1)}	21	{(6, 5,1), (5,4,1)}	24	{(6, 5,1), (5,2,1)}
25	{(6, 4,3), (5,4,3)}	28	{(6, 4,3), (5,3,2)}	31	{(6, 4,2), (5,4,3)}	34	{(6, 4,2), (5,3,2)}
26	{(6, 4,3), (5,4,2)}	29	{(6, 4,3), (5,3,1)}	32	{(6, 4,2), (5,4,2)}	35	{(6, 4,2), (5,3,1)}
27	{(6, 4,3), (5,4,1)}	30	{(6, 4,3), (5,2,1)}	33	{(6, 4,2), (5,4,1)}	36	{(6, 4,2), (5,2,1)}
37	{(6, 4,1), (5,4,3)}	40	{(6, 4,1), (5,3,2)}				
38	{(6, 4,1), (5,4,2)}	41	{(6, 4,1), (5,3,1)}				
39	{(6, 4,1), (5,4,1)}	42	{(6, 4,1), (5,2,1)}				
43	{(6, 3,2), (5,4,3)}	46	{(6, 3,2), (5,3,2)}	49	{(6, 3,1), (5,4,3)}	52	{(6, 3,1), (5,3,2)}
44	{(6, 3,2), (5,4,2)}	47	{(6, 3,2), (5,3,1)}	50	{(6, 3,1), (5,4,2)}	53	{(6, 3,1), (5,3,1)}
45	{(6, 3,2), (5,4,1)}	48	{(6, 3,2), (5,2,1)}	51	{(6, 3,1), (5,4,1)}	54	{(6, 3,1), (5,2,1)}
55	{(6, 2,1), (5,4,3)}	58	{(6, 2,1), (5,3,2)}				
56	{(6, 2,1), (5,4,2)}	59	{(6, 2,1), (5,3,1)}				
57	{(6, 2,1), (5,4,1)}	60	{(6, 2,1), (5,2,1)}				

3.2.2 Computation of Agency Cost

For each segment in the network, the agency cost (or the cost to implement each action, depending on whether it is a pavement or bridge) is simply a lookup function using the data in Table 3.5 based on the action selected to determine the unit cost. The unit costs are then multiplied by the appropriate factors reflecting the physical layout (length and number of lanes) of the segment. These factors include the discount factor – which discounts the cost at time t to the present value, and the maintenance cost rate – which measures the rate of change in maintenance costs after action. W. Zhou et al. (2022) provide the unit costs of each action in dollars per square meter. Therefore, the unit cost is multiplied by the length of the road (meters), the number of lanes and the width of a lane (meters). The total agency cost over the planning horizon is the present value of the costs over the planning horizon discounted at a specified discount factor γ.

Therefore, the total agency cost is: $\sum_{t=1}^{T} \gamma^{t-1} (c_1(a_t))$, where $c_1(a_t)$ are agency costs in year t for actions a_t. The various cost values that are used in the computation of the agency cost, $c_1(a_t)$, for pavement and bridge segments are presented in Table 3.5.

3.2.3 Computation of User Cost

W. Zhou et al. (2022) defined user costs as a function of the condition state i.e. for a given condition state of a segment, the expected user cost that will be incurred is determined. Like the agency cost, it is simply a look up function using Table 3.6 based on the condition state. Again, the unit costs are multiplied by the

appropriate factors. These factors include discount factor and user cost rate – which measures the rate of change in user costs after action. Like the costs for the actions, user costs are given in dollars per square meter.

Therefore, the total user cost is: $\sum_{t=1}^{T} \gamma^{t-1} (c_2(s_t))$, where $c_2(s_t)$ is the user costs in year t based on actions a_t. The various cost values that are used in the computation of the user cost for pavement and bridge segments are presented in Table 3.6.

Table 3.5: Agency costs of improvement actions on pavement and bridge segments (W. Zhou et al., 2022)

	Cost ($/m^2)	
Action	Pavement	Bridge
Do nothing	0	0
Minor repair	16	400
Major repair	68	1200

Table 3.6: User costs on pavement and bridge segments (W. Zhou et al., 2022)

	Cost ($/m^2)	
States	Pavement	Bridge
6	-	0
5	0	10
4	8	20
3	14	50
2	25	100
1	200	500

Table 3.7: Duration of actions on pavement and bridge segments (W. Zhou et al., 2022)

	Pavement		Bridge
Action	Days per lane-mile	Additional days per mile for shoulders, etc.	Days per bridge deck
Do nothing	0	0	0
Minor repair	3.5	1	12
Major repair	6.5	2	30

3.2.4 Computation of Disruption Cost

The disruption cost is the difference in the total travel time on the network without any actions (i.e. undisrupted network) and the total travel time on the same network with actions on the links (i.e. disrupted network). As the networks that will be explored in this study are relatively small compared with actual highway networks, each of the activities are assumed to be undertaken sequentially i.e. no two links can have activities carried out on them concurrently. The travel time on the network is found by determining the travel time on each link assuming a given origin-destination (OD) demand and user equilibrium. The solution requires the following data:

- OD demand whose value is set as input variable to the model. In this study, there can only be one origin-destination pair in the networks.
- Link performance properties for each link, including the free-flow travel time, the capacity and constants a and b, which are used in the link performance function to compute the traffic time on the link when estimating the network user equilibrium. The Bureau of Public Road (BPR) link performance function (Branston, 1976), expressed as: $T = T_o[1 + a(Q/c)^b$ where T is the traffic time on link, T_o is the free flow travel time on link, Q is the traffic volume on the link,

c is the capacity on the link, and a and b are calibration coefficients for the function.

The travel time is computed using a Python network user equilibrium routine (Moylan, 2023) which is based upon the Frank Wolfe Algorithm (Frank & Wolfe, 1956). The difference in the travel time is computed by assigning the traffic demand to the undisrupted network and the disrupted network separately, computing the travel times for both and subtracting the value for the undisrupted network from that of the disrupted network. The travel time difference is converted to cost equivalent by multiplying it by the number of users on the network and the value of time. All relevant data are contained in Table 3.3.

Therefore, the total disruption cost is:

$\sum_{t=1}^{T} \gamma^{t-1} (c_3(\boldsymbol{a_t}))$,

where $c_3(a_t)$ is the user costs in year t based on actions a_t.

As Zhou et al. (2022) noted, the disruption cost is excessively large, so, a traffic factor ρ is applied to account for a fraction of the disruption. The various cost values that are used in the computation of the disruption cost for pavement and bridge segments are presented in Table 3.7.

3.2.5 Total Cost over the Planning Horizon

The total cost over the planning horizon is the sum of the agency cost, the cost, the user cost, and the disruption. This is expressed as:

$\sum_{t=1}^{T} \gamma^{t-1} (c_1(\boldsymbol{a_t}) + c_2(\boldsymbol{s_t}) + \rho c_3(\boldsymbol{a_t}))$.

3.2.6 Monte-Carlo Simulation of Deterioration

The ability to determine the projected condition state of the link after implementing an action is critical to the computation of the costs. However, the deterioration of the links is not a deterministic process and is based on the transition probabilities of each condition state and action. These transition probabilities are represented as:

Pr_b ($S_{t+1}|S_t$, a_t) = Probability of a bridge being in state S_{t+1} given the bridge or segment was in state S_t and action a_t was performed.

Pr_k ($S_{t+1}|S_t$, a_t) = Probability of a pavement segment being in state S_{t+1} given the bridge or segment was in state S_t and action a_t was performed.

The transition probability matrices for the various actions for both bridges and pavements are adopted from W. Zhou et al. (2022) and presented in Table 3.8 and Table 3.9.

Monte-Carlo simulation is adopted to determine the condition state at time t+1. A random number between 0 and 1 is generated and the condition state is based on the inverse of the cumulative probability density function (CDF) for this random number. Mathematically, let U be a uniform random variable, defined as $U \sim \text{Uniform}(0,1)$; X be the corresponding random variable (i.e. condition state) whose distribution is to be sampled from; and $F(x)$ is the cumulative distribution function of the distribution of X such that $F(x) = P(X \leq x)$. The cumulative distribution of X is the probability that the sampled value of X is less than or equal to some number x. Since U is a probability distribution, the CDF can be rewritten as $F(x) = U$, so that the value of X can be obtained from the inverse of the CDF as $X = F^{-1}(U)$. This process was implemented in Python.

Due to the stochasticity in the value of the condition state, the process is repeated for 1000 iterations of the condition states based on a Monte Carlo simulation. The 1000 iterations stopping criterion was determined from preliminary experiments showing that successive iterations, on average, did not improve the previous outcome in cost by not more than 1%.

Table 3.8: Transition probability matrix for actions on pavements based on 5 IRI (m/km) states (Faddoul, Raphael, Soubra, & Chateauneuf, 2013; W. Zhou et al., 2022)

Do nothing					
States	5	4	3	2	1
5	0.840	0.121	0.039		
4		0.788	0.142	0.070	
3			0.708	0.192	0.100
2				0.578	0.422
1					1.000
Minor repair					
States	5	4	3	2	1
5	0.970	0.030			
4	0.850	0.120	0.030		
3	0.450	0.400	0.120	0.030	
2		0.450	0.400	0.120	0.030
1			0.450	0.400	0.150
Major repair					
States	5	4	3	2	1
5	1.000				
4	0.950	0.050			
3	0.800	0.200			
2	0.700	0.250	0.050		
1	0.450	0.350	0.200		

Table 3.9: Transition probability matrix for actions on bridges based on 5 IRI (m/km) states (Faddoul et al., 2013; W. Zhou et al., 2022)

	Do nothing					
States	6	5	4	3	2	1
6	0.850	0.090	0.060			
5		0.770	0.130	0.100		
4			0.780	0.140	0.080	
3				0.920	0.040	0.040
2					0.820	0.180
1						1.000
	Minor repair					
States	6	5	4	3	2	1
6	0.970	0.030				
5	0.850	0.120	0.030			
4	0.400	0.450	0.120	0.030		
3		0.400	0.450	0.120	0.030	
2			0.400	0.450	0.120	0.030
1				0.400	0.450	0.150
	Major repair					
States	6	5	4	3	2	1
6	1.000					
5	0.950	0.050				
4	0.800	0.200				
3	0.600	0.300	0.100			
2	0.400	0.400	0.200			
1	0.300	0.400	0.300			

3.3 Structure of the Models

With the building blocks discussed, the structures of the three models are presented in the following sections.

3.3.1 Predefined Threshold-based Tool

Similar to the widely adopted simple rule-based tools in DOTs, the predefined threshold-based tool uses a preset maintenance policy to compute the cost over the planning horizon for a highway network. Based on the set thresholds,

an action is selected. With the selected action, the agency cost, user cost, and disruption cost are computed, and the condition state must be updated based on the current state and the action selected. For each year through the planning horizon, the agency and user costs are computed for each segment, and the disruption costs is computed for the network. These costs are computed for one realization of the random condition state for each asset for each year through a Monte Carlo simulation run over many realizations of condition states. The algorithm for predefined thresholds-based tool is shown in Figure 3.1.

Algorithm 1 Predefined threshold-based tool

Input: Planning horizon (T), Number of segments (K),
Policy: $\{(\zeta_1, \zeta_2, \ldots, \zeta_{AKl}), (\sigma_1, \sigma_2, \ldots, \sigma_{ABl})\}$,
s_k^1 = condition state at $t = 1$, for each segment k,
Output: Life-cycle maintenance cost, user cost, disruption cost, and total cost
Initialize empty array for life-cycle agency cost, user cost, disruption cost, and total cost
for iter in iterations **do**
  Initialize agency_cost_iter = 0, user_cost_iter = 0,
  disruption_cost_iter = 0, total_cost_iter = 0
  for year t in T **do**
    for segment k in K **do**
      action_k ← select action based on the condition of segment k
      agency_cost_k ← Compute agency cost for action action_k
      s_k^{t+1} = Update condition of segment k after applying action_k
      user_cost_k ← Compute user cost resulting from action_k
      disruption_cost_k ← Compute disruption cost due to action_k
      total_cost_k ← agency_cost_k + user_cost_k + disruption_cost_k
      agency_cost_iter += agency_cost_k
      user_cost_iter += user_cost_k
      disruption_cost_iter += disruption_cost_k
      total_cost_iter += total_cost_k
    end for
  end for
end for
Compute average of all agency_cost_iter, user_cost_iter, disruption_cost_iter, total_cost_iter and return as **Output**

Figure 3.1: Algorithm for predefined thresholds-based tool

3.3.2 Optimal Threshold-based Tool Optimized for Total Cost

On the higher end of the complexity spectrum, a more complex tool is developed based on the same concepts as the predefined thresholds-based tool, except that in this case, the threshold is not predefined. Instead, the algorithm searches through all feasible policies and determines the one that produces the optimal total cost (where the total cost is the sum of the agency cost, user cost, and disruption cost) over the planning horizon as well as the corresponding cost components. For this tool, each run of the Monte-Carlo simulation requires the solution of the network equilibrium problem to determine the disruption cost. The algorithm for this complex tool is shown in Figure 3.2.

Algorithm 2 Optimal threshold-based tool optimized for total cost

Input: Planning horizon (T), Number of segments (K),
Set of policies:

$$\begin{bmatrix} \{\zeta_{1,1}, \zeta_{1,2}, \ldots, \zeta_{1,AKl}, \sigma_{1,1}, \sigma_{1,2}, \ldots, \sigma_{1,ABl}\} \\ \{\zeta_{2,1}, \zeta_{2,2}, \ldots, \zeta_{2,AKl}, \sigma_{2,1}, \sigma_{2,2}, \ldots, \sigma_{2,ABl}\} \\ \vdots \\ \{\zeta_{I,1}, \zeta_{I,2}, \ldots, \zeta_{I,AKl}, \sigma_{I,1}, \sigma_{I,2}, \ldots, \sigma_{I,ABl}\} \end{bmatrix}$$

$s_k^1 =$ condition state at $t = 1$, for each segment k,
Output: `optimal_policy`, `corresponding_cost_components`
Initialize `optimal_total_cost` to `inf`
for each `policy_i` in `policies` **do**
    `policy_total_cost` ← Extract from `Algorithm 1` using `policy_i`
    if `policy_total_cost` < `optimal_total_cost` **then**
        `optimal_policy` ← `policy_i`
        Save `corresponding_cost_components`
        Update `optimal_total_cost` with `policy_total_cost`
    end if
end for

Figure 3.2: Algorithm for optimal threshold-based tool optimized for total cost

3.3.3 Optimal Threshold-based Tool Optimized for Agency Plus User Costs

Based upon the hypothesis that disruption in the network may range from very low to very high, such that could potentially cause the total cost to be very comparable to the outcomes from the threshold-based model if disruption is negligible, or the complex thresholds-based tool if disruption is considerably high a third tool is proposed. One scenario when this tool might be applicable is when the agency during budgeting decisions, wants to make projections based on the optimal agency plus user costs of maintenance which is well within their control. The tool is similar to the second tool except that the policy and the four cost components produced are based on the policy that results in the least agency plus user cost. As disruption cost is not considered, the solution does not require the solution of the network equilibrium problem for each run. The algorithm for this tool is shown in Figure 3.3.

Algorithm 3 Optimal threshold-based tool optimized for agency plus user cost

Input: Planning horizon (T), Number of segments (K),
Set of policies:

$$\begin{bmatrix} \{\zeta_{1,1}, \zeta_{1,2}, \ldots, \zeta_{1,AKl}, \sigma_{1,1}, \sigma_{1,2}, \ldots, \sigma_{1,ABl}\} \\ \{\zeta_{2,1}, \zeta_{2,2}, \ldots, \zeta_{2,AKl}, \sigma_{2,1}, \sigma_{2,2}, \ldots, \sigma_{2,ABl}\} \\ \vdots \\ \{\zeta_{I,1}, \zeta_{I,2}, \ldots, \zeta_{I,AKl}, \sigma_{I,1}, \sigma_{I,2}, \ldots, \sigma_{I,ABl}\} \end{bmatrix}$$

$s_k^1 =$ condition state at $t = 1$, for each segment k,
Output: `optimal_policy`, `corresponding_cost_components`
Initialize `optimal_agency_user_cost` to `inf` (sum of agency and user cost)
for each `policy_i` in `policies` **do**
  `policy_agency_user_cost` ← Extract from `Algorithm 1`
  if `policy_agency_user_cost` < `optimal_agency_user_cost` **then**
    `optimal_policy` ← `policy_i`
    Save `corresponding_cost_components`
    Update `optimal_agency_user_cost` with `policy_agency_user_cost`
  end if
end for

Figure 3.3: Algorithm for optimal threshold-based tool optimized for agency and user costs

3.4 Concluding Remarks

From the discussion in the previous sections, it is evident that the variables and parameters required to implement the program are the same, except for the fact that the complex tools require as inputs all 60 feasible maintenance policies, while the simple threshold tool requires just one prespecified tool. For the simple tool, the policy adopted is {[5,3,2], [6,5,2]} based on the findings of W. Zhou et al. (2022).

The added complexities of the optimal threshold-based tools come at the expense of computational requirements. The fact that all feasible policies must be explored in the realization of the optimal costs means that at the minimum, 60 times

more computing time is required. This can be very large depending on the size of the highway networks explored. Specific data on the computational burden is presented in Section 6.3.1.

Chapter 4

WHAT DO LOCAL AND GLOBAL SENSITIVITY ANALYSES TELL AGENCIES ABOUT ASSET MANAGEMENT DECISION SUPPORT TOOLS?

4.1 Introduction

Transportation infrastructure is a critical infrastructure system, irrespective of location, ownership, or institutional responsibilities, as it provides a platform upon which economic and other societal activities are built. Although this infrastructure is built to last for decades, frequent use and exposure to everyday and extreme environmental conditions cause these systems to deteriorate over time necessitating routine maintenance and rehabilitation to prolong their useful lives. Scheduling and prioritizing these maintenance and rehabilitation activities are not easy for asset managers due to limited resources, the many decision alternatives (different actions, different types of infrastructure, and different locations) to choose from, and interactions among the cost impacts and user disruptions over the planning horizon.

Asset managers develop or adopt and then use decision support tools, ranging from simple rule-based ranking methods to complex mathematical models, to address the various multi-faceted decision challenges encountered in infrastructure engineering. Models and decision frameworks are based on techniques ranging from single-criteria, multi-criteria optimization, and dynamic

programming to multilevel optimization and Markov decision processes (Zhou et al., 2022). Typically, the simple rule-based methods use a set of predefined rules, such as those used in Ontario (Wei & Tighe, 2004), to evaluate and prioritize the options. On the other hand, complex mathematical models, which are often based on optimization techniques (Chen & Bai, 2019), seek an optimal strategy or policy from a defined objective function over a set of decision variables and given constraints. Such models identify strategies or policies accounting for the various complex challenges encountered in infrastructure management where maintenance and rehabilitation activities are strategically planned from a pool of choices with competing objectives limited by available resources within a specified planning horizon.

Despite the popularity of optimization techniques for decision-making in complex infrastructure systems, the applicability of many of these models is sometimes questionable as there seems to be a lack of fidelity in the decision outcomes of the models (Z. Wang & Pyle, 2019). This is because most of the models are a black box of complex mathematical or programming expressions that are difficult to understand by the decision-makers who use the models. Moreover, how the model parameters interact to create decision outcomes from the models cannot be easily discerned.

Sensitivity analysis is commonly used to help calibrate and evaluate decision support tools by exploring how changes in inputs (both parameters and input variables) impact model outcomes. Sensitivity analysis is also used to focus attention on the value of input variables that may be uncertain or choosing parameter values that reflect the context or situation. Such sensitivity analysis has

concentrated on local sensitivity analysis, which explores the impact of changes in inputs one by one. Global sensitivity analysis, which determines the variance contribution of the inputs to the variance of the output, and helps identify the most influential parameters, is used to better understand the interactions among parameters.

The objective of this study is to explore the role of local and global sensitivity analysis, in identifying influential parameters and calibrating models in a transportation infrastructure asset management context. An infrastructure asset maintenance prioritization and scheduling problem is selected as a case study to demonstrate the methods. This decision framework, based on Zhou et al. (2022), enumerates all feasible policies to determine the most cost-effective improvement decisions over a specified planning horizon considering the impact of capacity losses during improvement action execution, traffic impacts of improved serviceability after maintenance measured by road user costs, and uncertain deterioration mechanisms across multiple bridges and pavements. Adding to the complexity of the model, several input parameters are required for implementation and the appropriate value is not always clear. Also unclear is the parameters' influence on the model outcomes. Capturing the influence of parameter selection in the model outputs helps to calibrate the model and can reduce the model complexity if parameters are not influential. Hence, there is a need for sensitivity analysis to understand the role of each parameter, as well as their interaction effects, therefore aiding model calibration (Judd, 2010).

The paper is structured as follows. The next section provides the relevant background on model calibration and sensitivity analysis including relevant

examples of sensitivity analysis from the literature. The subsequent section describes the methodology and case study. The results of the analysis are then presented. The paper concludes with a discussion of the results and how they are used. The paper demonstrates the role of local and global sensitivity analysis in calibrating and evaluating complex models, and in parameter selection.

4.2 Background and Literature Review

Model calibration determines the parameter value(s) of a model such that these values are like the observed outcomes (Shewmaker, Chrysanthopoulou, Iskandar, Lake, & Jutkowitz, 2022). In some systems, however, due to the simplification of the models representing them, observing the outcomes (i.e., targets) from the models for calibration may not be feasible. Moreover, models representing complete systems, such as infrastructure systems, use parameters that can be selected to reflect context, such as current economic conditions, or environmental attributes. Choosing parameter values is an important part of model calibration. However, the combined impacts of these parameters are not always well understood when the models are designed. To help calibrate such models, the models can be viewed as computational experiments for exploring numerous combinations of potential scenarios, represented by inputs or parameters, and outcomes, represented by output variables. The focus then shifts from the prediction of outcomes of scenarios to discovering scenarios (in this case, combinations of model inputs) that result in consequential and inconsequential outcomes (Reed et al., 2022). This exploratory process is facilitated by a well-structured sensitivity analysis.

Sensitivity analysis (SA) explores the relationships between the input variable(s) or parameters, and the associated output variable(s) for a model. It is the study of how variability in the model outputs can be quantified and attributed to different sources of variability in the inputs and choices for the model parameters (Reed et al., 2022). SA methods can be classified into three types, namely: screening methods, local sensitivity methods, and global sensitivity methods (Alhossen et al., 2019). Screening methods are used to analyze qualitatively the sensitivity of model outputs to identify the non-influential inputs (variables or parameters) through a small number of model evaluations. Local sensitivity methods are used to analyze quantitatively the changes in model outputs with a small variation of the input around a fixed value in such a way that each variable is varied one-by-one, while setting others to some fixed values. Global sensitivity analysis methods are used to analyze quantitatively the sensitivity of model outputs to variations in the inputs by varying all the inputs over entire ranges to decompose the variance in the outputs based on the variances in the inputs (Alhossen et al., 2019). Global sensitivity analysis methods are preferred to local sensitivity methods because they capture interactions among the input variables and are well-suited for non-linear models where these interactions are not easily understood. Sobol's method, a variance-based sensitivity analysis method, is widely used (Iooss & Lemaître, 2015). The disadvantage of this method is that it is computationally intensive. However, other methods are difficult to interpret or have other estimation problems (Iooss & Lemaître, 2015). In this research, we use Sobol's method recognizing future opportunities to explore other methods for global sensitivity analysis. Sobol's method is used to uncover the behavior of the model as parameters

in the model change and by extension help to understand the implications of the parameter choices.

The applications vary across disciplines. For example, in watershed modeling, Van Werkhoven, Wagener, Reed, and Tang (2009) applied global sensitivity analysis as a tool to decrease the parametric dimensionality of a multi-objective model calibration problem. They showed that with a coupled, multi-objective sensitivity and calibration analysis using Sobol's method, it is possible to adequately capture the differences between watersheds during model calibration and, hence, maximize the value of the time series data available for model calibration.

In transportation studies, the proliferation of complex models, which are often computationally inefficient, and designed for solving multi-dimensional problems, has resulted in the need for model evaluation to either reduce the complexities by decreasing the number of parameters in the model or discover generalizable patterns from the input-output combinations from the model. Yet, despite the importance of sensitivity analysis in terms of the model correctness, prediction accuracy, and reproducibility of results, it is not uncommon to find that proper sensitivity analysis is not undertaken (Ge, Ciuffo, & Menendez, 2014). For example, a survey of traffic simulation models found that on average 33% of users of traffic simulation models, such as VISSIM, Aimsun, and Paramics, did not perform sensitivity analysis (Brackstone, Montanino, Daamen, Buisson, & Punzo, 2012; Ge et al., 2014).

Another application of Sobol's method explored the disaggregation of the variations in the benefits of transit state of good repair (SGR) caused by

uncertainties in travel demand predictions. Wang, Carrel, and Robert (Y. N. Wang, Carrel, & Robert, 2021) noted that although the SGR benefit is largely dependent on the travel demand, the entire range of SGR benefits involves complex interactions between the travel demand and several other parameters for which values must be chosen to reflect the context. This makes it onerous to identify the amount of variance in the SGR benefits due to the inadequate understanding of travel demand impacts. They proposed an approach based on Sobol's method to estimate the total variance of anticipated benefits of transit SGR that could be associated with the uncertainties in the variables that influence travel demand. They estimated the contribution of each variable to the estimated total variance.

In infrastructure systems analysis, no application of Sobol's method for parameter sensitivity analysis has been found, while traditional local-sensitivity methods are still widely used (for example, (Ferry, Delorit, & Chini, 2022; Mishalani & Olayé, 1999; Song, Thatcher, Li, McHugh, & Wu, 2021). To address this gap in the literature and the challenges (Atolagbe & McNeil, 2023c; Z. Wang & Pyle, 2019) involved in the calibration and evaluation of, and parameter selection for infrastructure decision support tools, this paper demonstrates the role of local and global sensitivity analysis. Table 4.1 summarizes the examples of studies using Sobol's method in other fields, the examples of local sensitivity analysis infrastructure decision-making, this study, and their contributions to the literature in the context of this study.

Table 4.1: Contribution of this and related work

Application Area	Contribution	Sensitivity Analysis		Source
		Local	Global	
Watershed models	Reduce the dimensionality of the problem	✓	✓	(Van Werkhoven et al., 2009)
Charge generation and transport in dielectrics	Selection of conditions for efficient parameter estimation	✓	✓	(Alhossen et al., 2019)
Traffic simulation	Parameter estimation	✓	✓	(Brackstone et al., 2012) (Ge et al., 2014)
Benefits of transit state of good repair	Influence of variables on travel demand	✓	✓	(Y. N. Wang et al., 2021)
Infrastructure decision-making	Examples of local sensitivity analysis	✓		(Ferry et al., 2022) (Mishalani & Olayé, 1999) (Song et al., 2021)
Bridge and pavement asset maintenance prioritization and scheduling	Model calibration, evaluation and parameter selection, particularly the value of global sensitivity analysis.	✓	✓	This study

Given the complexity of the infrastructure decision support tools, which are due to the complexity of the infrastructure systems themselves, a more robust sensitivity analysis as can be obtained by Sobol's method can offer insights into the relative importance of the model parameters and their relative impact. Sensitivity analysis also supports model calibration and evaluation.

The method considers complex and nonlinear factor interactions when calculating sensitivity indices, employs highly sophisticated sampling methods, i.e., Sobol sampling, and enables the computation of three types of sensitivity indices (first order, higher order, and total order) all of which provide different information about the model sensitivities (Reed et al., 2022). First-order Sobol's sensitivity indices measure the proportion of variance in the model output that is attributable to an input parameter or variable independently. Higher order (e.g., second-, and third-orders) Sobol's sensitivity indices represent the model output variances attributable to the interaction between two or more parameters, while total order Sobol's sensitivity indices measure the variance in model output that is attributable to an input parameter and its interactions with other parameters or variables (Reed et al., 2022).

4.3 Methodology and Its Application to a Case Study

To explore the role of sensitivity analysis in identifying influential parameters and calibrating models in a transportation infrastructure asset management context, a quantitative analysis is conducted for a case study. This sensitivity analysis focuses on the input parameters rather than input variables and includes a local sensitivity analysis, for comparison with current practice, as well as the global sensitivity analysis. This section describes the case study modified from the literature, the methods used for the local and global sensitivity analysis, and the experimental design.

4.3.1 Case Study Model

The case-study model seeks to solve a multi-class asset maintenance prioritization and scheduling problem considering the traffic impacts to minimize the total cost of improvement investment, user costs, and traffic delays due to the downtime resulting from the implementation of the actions over a specified planning horizon. The framework is based upon a bilevel optimization that seeks an optimal policy for prioritizing maintenance of infrastructure assets (pavements and bridge decks) considering the variability in the deterioration of assets and the traffic impacts from deteriorated pavements and bridge decks, as well as reduced capacity during downtime due to the execution of maintenance actions. Using the formulation presented in (W. Zhou et al., 2022), we determine the optimal policy by evaluating all feasible policies. A Python program was developed to determine the optimal policy and complete the local and global sensitivity analysis.

In this study, the model is constructed as follows:

- Given a transportation network of k segments, a set of condition states S (for pavements, values of 5 through 1, and for bridges, values of 6 through 1), a set of implementable actions A (do nothing, minor repair, and major repair), a defined planning horizon T, and N feasible policies where each policy represents the condition states at which each action ai is triggered. A policy is a set of thresholds for pavements and bridges, $\{[s_{p1}, s_{p2}, s_{p3}], [s_{b1}, s_{b2}, s_{b3}]\}$, where s_{pi} is the pavement condition at which action ai is triggered and s_{bi} is the bridge condition at which action ai is triggered.
- For each year within the planning horizon, we assess the condition state of each segment against the policy and decide on the appropriate action.

- The cost of making this decision is assessed as the agency cost. There is a user cost implication due to this decision which is also assessed. In addition to this, the implementation of the action will also induce a network-wide disruption cost depending on the importance of this segment in the network. All these three cost components are added as the total cost for the decision made on that segment during that year.
- This process is repeated for each pavement and bridge segment, and each year over the entire planning horizon while progressively summing the discounted individual cost components.

Five model parameters are introduced for model calibration: 1) discount rate, which is a function of the time value of money, is applied to discount the costs to the present value as we progress through the planning horizon; 2) deterioration rate is applied to the pavement condition states to account for deterioration when no minor or major treatment action is carried out; 3) traffic delay factor is applied to the disruption cost to account for the allowable disruption the decision maker wants to allow during the planning process; and 4) user cost rate and 5) maintenance cost rate, applied respectively to the user cost and agency cost to account for the rate of change in these costs after actions are done.

To account for the uncertainty in the condition states, represented by a Markov deterioration model, this process is repeated over 1000 times, and the averages for each of the four cost components are accessed as the lifecycle cost for each policy. Furthermore, the process is repeated for all N feasible policies, and the values corresponding to the minimum total costs are taken as the optimal lifecycle

costs while the corresponding policy that yields them is taken as the optimal policy. The implementation is documented in (Atolagbe & McNeil, 2024a).

The model was evaluated using a toy traffic network from the literature (Medury & Madanat, 2013) with eleven pavement sections and modified (W. Zhou et al., 2022) to incorporate two bridges as shown in Figure 4.1. Segments 5-8 have one lane, 4 and 9-11 have two lanes, and 1- 3 have four lanes. Free-flow speeds are presumed to be 55 miles per hour (mph) along all segments and all segments are presumed to be five miles in length. All data are based on (W. Zhou et al., 2022) but were modified to reflect the network capacity and a realistic period of disruption.

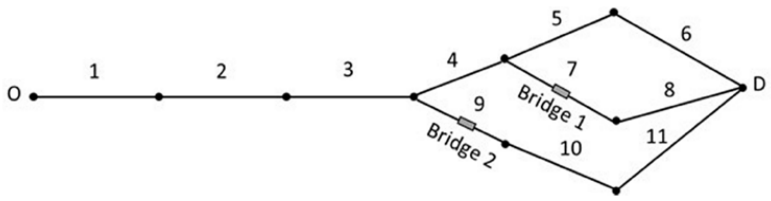


Figure 4.1: Case-study roadway network structure (W. Zhou et al., 2022)

In the study of parameter sensitivities, we consider the model as a black box whose details are unknown to the asset manager who wants to use the model. We are interested in the sensitivities of the four model decision outcomes i.e., maintenance cost, user cost, traffic delay cost, and total cost over the planning horizon to the seven input parameters i.e., deterioration rate, user cost rate, maintenance cost rate, discount rate, and the traffic factor. Therefore, we focus on

the input parameters and outputs of the model and attempt to understand the direct relationships and interactions among them. A summary of the input parameters (ranges and definitions) is presented in Table 4.2. The default values and ranges (upper and lower bounds) for the input parameters are based on common practice and rational assumptions. The pavement deterioration rate modifies a Markov transition probability matrix. Further documentation is provided in (Atolagbe & McNeil, 2024a).

4.3.2 Local Sensitivity Analysis

Local sensitivity analysis or the one-at-a-time technique, is performed by varying the parameters around specific reference values (Reed et al., 2022). It involves changing the value of an input parameter of interest over its range while keeping the value of all other parameters constant and observing the corresponding outputs for each value. Typically, the slope of the model's response to small changes in the nominal values of the input parameters provides the sensitivity of the model's response to the input. Note that, these nominal points are selected as the best estimates for that parameter (X. Zhou & Lin, 2008). Thus, the sensitivity of the outputs to variations in each parameter is dependent on the values chosen for the other parameters. These values are based on knowledge of the context or similar problems and are often the values considered to be the best estimate of the actual value.

Local sensitivity is undertaken for two situations. The first situation is based on the optimal policy determined using the default parameter values. The second assesses the sensitivity of the optimal policy to the variation in the parameters. That

is, the optimal policy may change when one or more parameters change. Both situations assess the changes in the objective function (and its component costs) to changes in the parameters.

Table 4.2: Parameters for the sensitivity analysis of the model

Parameter	Default Value	Range	Definition
Deterioration rate	0.05	[0.01, 0.1]	Rate of deterioration of the pavement assets, a parameter in the Markov deterioration model. Only applies to the do-nothing alternative.
User cost rate	1	[1.0, 2.0]	Rate of change in user cost after action.
Maintenance cost rate	1	[0.75, 5.0]	Rate of change in maintenance cost after action.
Discount rate	0.05	[0.01, 0.1]	Discount rate for time-value of money.
Traffic factor	0.05	[0.01, 0.1]	Weight parameter for traffic delay, >0 (with the highest value of 1) to account for traffic delay costs or =0 if traffic delay costs are to be excluded.

4.3.3 Global Sensitivity Analysis

Consider a decision support model that represents a system, such as a complex infrastructure system. Typically, such a model requires a set of input variables and parameters $x_1, x_2, \dots, x_n$, and one or more output variables $y_1, y_2, \dots, y_p$. The input variables represent the problem context or application and reflect the situation. These variables include usage, condition, and capacity. The

input parameters represent the type of problem and are typically chosen based on past experiences. The parameters include unit costs, activity duration, time value of money, and value of time. Outputs include the costs over the planning horizon. For complex models, the relationship between the input and the output sets may not be easily observable as they are often based upon non-linear mathematical expressions whose evaluations are difficult to implement, sometimes even with computer programs. Understanding the variabilities in the outputs due to the inputs can be useful for calibrating and refining such decision models. As such, it is often desirable to study the sensitivity of the outputs to the changes in the input parameters. Sobol's method is used for this purpose.

Sobol's method, a global sensitivity analysis method, is based on the hypothesis that the specified input parameters of a model contribute differently to the variations in the model outcomes, and therefore, if the variance in the output can be decomposed and analyzed for each input, it is possible to determine the sensitivity of the model outcomes to the input parameters (Reed et al., 2022; Saltelli, Tarantola, Campolongo, & Ratto, 2004; Sobol, 2001).

To apply the Sobol method to the case study, the following methodology is used as documented in the literature (Alhossen et al., 2019; Baudoin et al., 2016). Sobol's method uses the following notation:

$f: y_k = f(x_1, x, \dots, x_n)$	non-linear function that represents a complex decision model
y_k	k^{th} output from the model
x_i	i^{th} input parameter to the model

$Var(y_k \mid x_i = x^*)$ conditional variance of y_k with respect to x_i , that is, the influence of an input variable x_i on the outcome variable y_k, by fixing the value of x_i at some value x^* while other input variables are varied

$Var(y_k)$ total variance in the output y_k,

A comparison between the estimates of $Var(y_k \mid x_i = x^*)$ and $Var(y_k)$ can be used to infer the impact of the input x_i on the output y_k as follows: if both $Var(y_k)$ and $Var(y_k \mid x_i = x^*)$ are the same, then the variable x_i does not account for any variations in the output and so does not have an impact on it; if however $Var(y_k \mid x_i = x^*)$ is less than $Var(y_k)$, then x_i does have an impact on the output y_k. But it is important to consider that x_i is not fixed and can take any value over its range of possible values. This is accounted for by taking the expectation E of the variances over all possible values of x_i, that is, $E[Var(y_k \mid x_i)]$. This quantity can be related to $Var(y_k)$ through the total variance formula as shown in Equation 4.1:

$$Var(y_k) = Var(E[y_k \mid x_i]) + E[Var(y_k \mid x_i)] \quad (4.1)$$

In Equation 4.1, since $Var(y_k)$ is always constant, when $E[Var(y_k \mid x_i)]$ is small, $Var(E[y_k \mid x_i])$ will be large suggesting that more of the variations in $Var(y_k)$ is captured in $Var(E[y_k \mid x_i])$ thus implying that y_k is sensitive to x_i, and vice-versa. Thus, it is possible to also use $Var(E[y_k \mid x_i])$ instead of $E[Var(y_k \mid x_i)]$ as a measure of the sensitivity of y_k to x_i as shown in Equation 4.2:

$$S_i = \frac{Var(E[y_k \mid x_i])}{Var(y_k)}, \tag{4.2}$$

where S_i is the sensitivity index which is a measure of the sensitivity of y_k to x_i. In Equation 4.2, it is expected that when $Var(E[y_k \mid x_i])$ is large, S_i is also large indicating high sensitivity, and vice-versa. This measure, S_i, for each input variable, x_i, is referred to as the Sobol's first-order sensitivity index (Alhossen et al., 2019; Baudoin et al., 2016).

It is also possible to compute higher-order sensitivity indices to reflect the amount of variation captured by combinations of two or more input variables. This enables us to understand the impacts of interactions among the input variables on the output. For instance, the second-order indices measure the sensitivity of the outputs to the interactions between pairs of input variables. If we rewrite the expression for first-order indices in Equation 4.2 as Equation 4.3:

$$S_i^1 = \frac{Var(E[y_k \mid x_i])}{Var(y_k)} \tag{4.3}$$

Then second order indices can be computed as shown in Equation 4.4:

$$S_{i,j}^2 = \frac{Var(E[y_k \mid x_i,x_j]) - Var(E[y_k \mid x_i]) - Var(E[y_k \mid x_j])}{Var(y_k)} \tag{4.4}$$

Considering the first order and higher order indices, it is possible to compute the total variance contribution due to each of the input variables. These estimates are called total sensitivity indices S_i^T, and can be defined as the sum of all the Sobol's indices associated with input variable x_i as shown in Equation 4.5:

$$S_i^T = S_i^1 + \sum_{j \neq i}^{n} S_{i,j}^2 + \cdots \quad (4.5)$$

For most applications, the first order, second order, and the total indices are considered (Alhossen et al., 2019).

Because Sobol's method accounts for the complex interaction effects among the input parameters, it is a desirable technique for identifying the input parameters that most impacts the model outcomes and isolate them from those that have less or no significance on the output, without underestimating the significance of any of the variables *a priori*.

4.3.4 Experimental Design

Local sensitivity analysis was conducted using the one-at-a-time sampling, where an input variable or parameter whose impact on the model output is being measured is varied over its range while a fixed value is selected for each of the remaining input variables. In this study, we utilized the default and ranges of values presented in Table 4.2 to define the lower and upper bounds for each input variable. For example, to study the sensitivity of the model outcomes to the pavement deterioration rate, the deterioration rate is varied over its specified range from 0.01 to 0.1, while the remaining input parameters are set to their default values.

The implementation of Sobol's method, on the other hand, involves the following steps: (1) definition of the input variables and parameters, and their corresponding lower and upper bounds, (2) generation of input data sets as different combinations of the variables and parameters over the defined ranges, (3) running

of the model with the input sets and obtain corresponding outputs, and (4) computing Sobol's indices using the input-output sets, and using the indices to describe the variance contribution of the input variables on the output variables (Baudoin et al., 2016). Details and the code used to implement the methods are provided in (Atolagbe & McNeil, 2024a).

Successful implementation of Sobol's method, as with other methods, requires adequate sampling of the input space. Sobol's method commonly uses the Saltelli sampling scheme to generate the input space (Reed et al., 2022). A detailed explanation of the Saltelli sampling scheme can be found in (Saltelli, 2002; Saltelli et al., 2010). The sampling schedule draws from continuous uniform distributions to provide efficient estimates of the variance. In this case study, both the Saltelli sampling scheme and Sobol's analysis were implemented in Python using the SALib library (Herman & Usher, 2017). The input space was generated using the lower and upper bounds defined in Table 4.2. Choosing the right number of samples for the experiment can be challenging. Typically, the sample size required for performing a correct Sobol's sensitivity analysis depends on (1) the complexity of the model, and (2) the number of parameters (X. Y. Zhang, Trame, Lesko, & Schmidt, 2015). For models with fewer than 20 parameters, a sample size of (N=1000) can be used (X. Y. Zhang et al., 2015). This value has also been favored in some previous studies for estimating Sobol's indices correctly (Gan et al., 2014; Gatel, Lauvernet, Carluer, Weill, & Paniconi, 2019).

In this study, a total number of 1536 input sets were generated based on the Saltelli sampling scheme (Herman & Usher, 2017). Figure 4.2 depicts the

variability in the generated samples and shows that the range is uniformly covered for three of the input parameters and variables.

The input sets were used to run the decision model in succession and the corresponding outputs for each run were stored in such a way that a new set of input-output combinations were created. In other words, for each combination of input variables, there is a corresponding group of outcome variables namely: user cost, agency cost, delay cost, and total cost. The sensitivities of each of these output variables to the input parameters were performed differently using the SALib and the generated Sobol's indices are analyzed next.

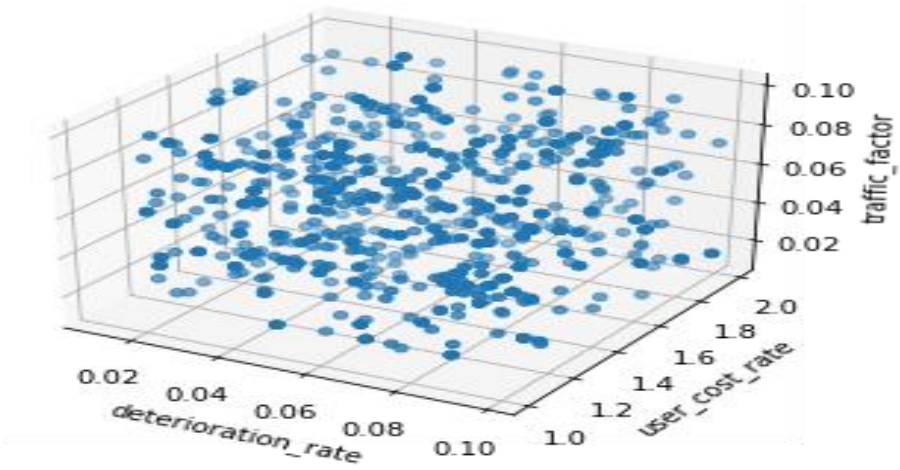


Figure 4.2: Saltelli sample space of three of the input parameters

4.4 Results and Discussion

The results are reported separately for local (one-at-a-time method) and global (Sobol's method) sensitivity analysis. In each case, costs over the planning

horizon, in terms of the total cost and each of its components, maintenance cost, user cost, and traffic delay cost are reported.

4.4.1 One-at-a-time Method

The results for the local (one-at-a-time) sensitivity analysis, where the sensitivities of each of the four output variables to each of the five input parameters are explored independently, are shown in Figure 4.3 for both the situation in which the given optimal policy is based on the default values of the parameters (shown by the dashed lines) and where the optimal policy may change with each change in the value of a parameter (shown by the solid lines).

First, given the optimal policy, {[5,3,1],[6,5,1]}, determined using the default values, consider the change in outputs when the input parameters vary. As the deterioration rate (Figure 4.3a), user cost rate (Figure 4.3b), and maintenance cost rate (Figure 4.3c) increase, the objective function (total costs over the planning horizon) and the component costs increase as expected. In general, the total costs increase monotonically, although for some input parameters, the relative contributions of the user cost and agency cost to the total cost change. The results also show that the range for the maintenance cost factor and the impact on total cost are much greater than for other factors suggesting that some additional attention should be paid to this parameter. As the discount rate (Figure 4.3d) increases, total costs go down as the present value decreases as expected. There is a minimal change in the traffic delay costs (Figure 4.3e) as the toy network is not congested (origin-destination flow is 3500 vehicles per hour). Therefore, in this case, the traffic factor has no impact on the outputs.

Next, consider the change in outputs when the input parameters vary, and the optimal policy is determined for each new parameter value. The results are very similar to the first situation. Although the policy changed in almost 75% of the 51 different variations of the input parameter values explored, the magnitude of the change in the objective function was typically 1-2% with a maximum of 4.4% with a maintenance cost factor of two. Except for increases in the maintenance cost rate of two or higher (seven cases), all policy changes involved changing only the threshold for major repair. Furthermore, variations in relative values of the user and agency costs were common. For example, for a user cost rate of 1.1 (that is, user costs increase by 10%), the optimal policy is {[5,3,2],[6,5,1]} rather than {[5,3,1],[6,5,1]}, and user costs increase but agency costs decrease.

As noted, this analysis was based on an uncongested network assuming a flow of 3500 vehicles per hour. The analysis was repeated for flows of 5000 vehicles per hour and 8000 vehicles per hour. Focusing on changes in parameter values less than 100% of the default value, Figure 4.4 shows the percentage in the total costs as a function of the percentage change in the parameter value for flows of 3500 and 8000 vehicles per hour. Based on the relative slopes, the costs are most sensitive to changes in the maintenance cost rate and the discount rate. In the more congested network (Figure 4.4b) the traffic factor was more important. Furthermore, for the more congested network, the optimal policy varied more between scenarios underscoring the importance of selection of the appropriate parameters.

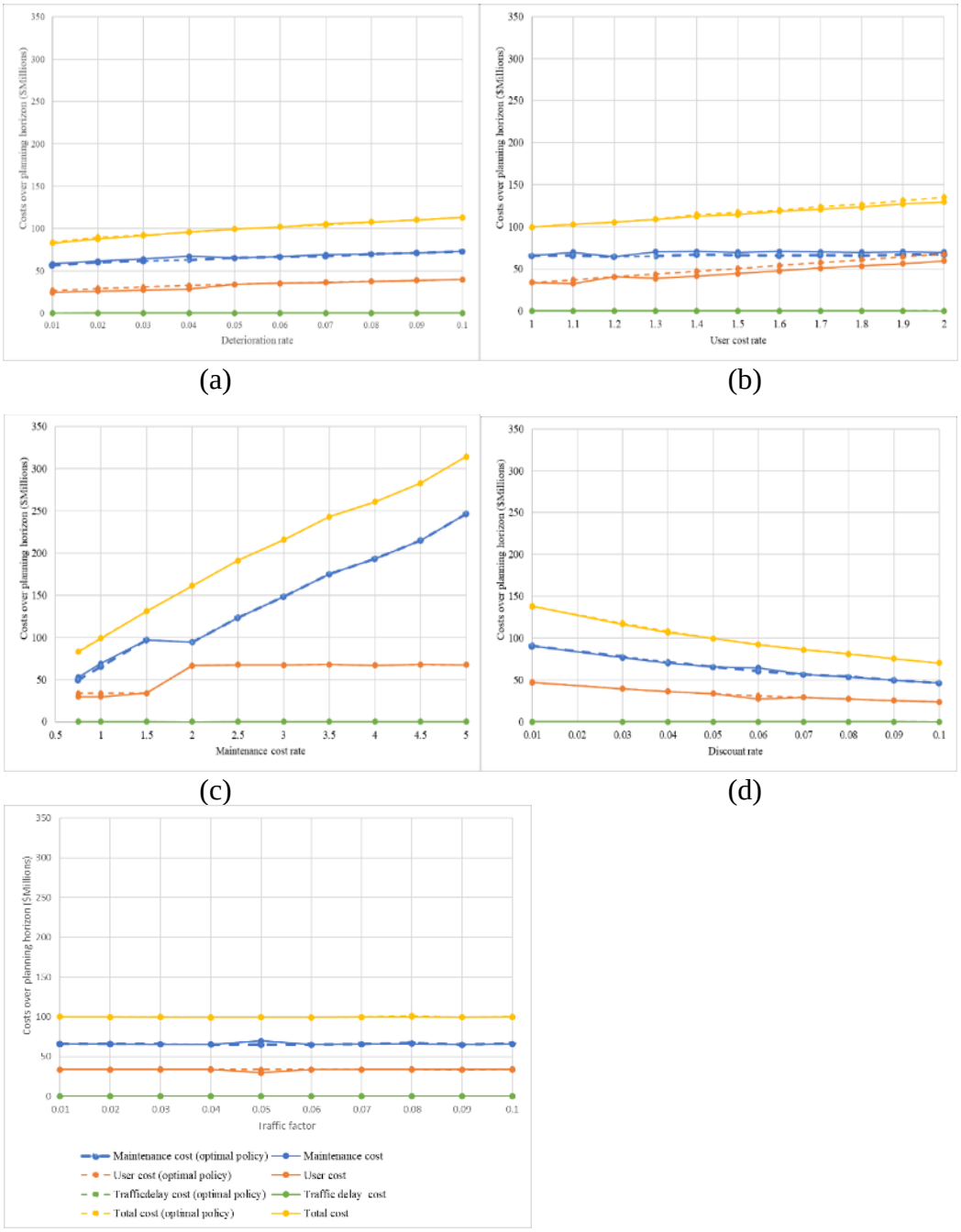
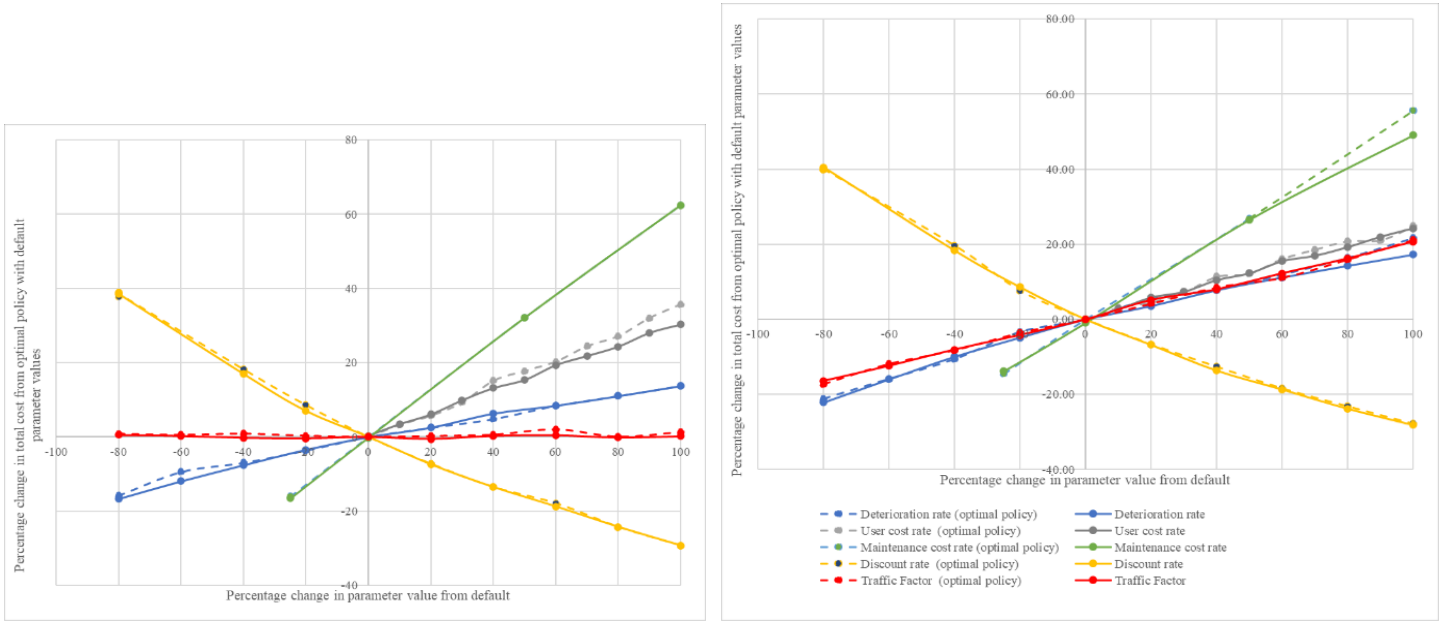


Figure 4.3: Sensitivity of the model output lifecycle costs to (a) deterioration rate (b) user cost rate (c) maintenance cost rate (d) discount rate (e) traffic factor



b)

Figure 4.4: Percentage change in total cost to percentage changes in parameter values for a) 3500 vehicles per hour, and b) 8000 vehicles per hour

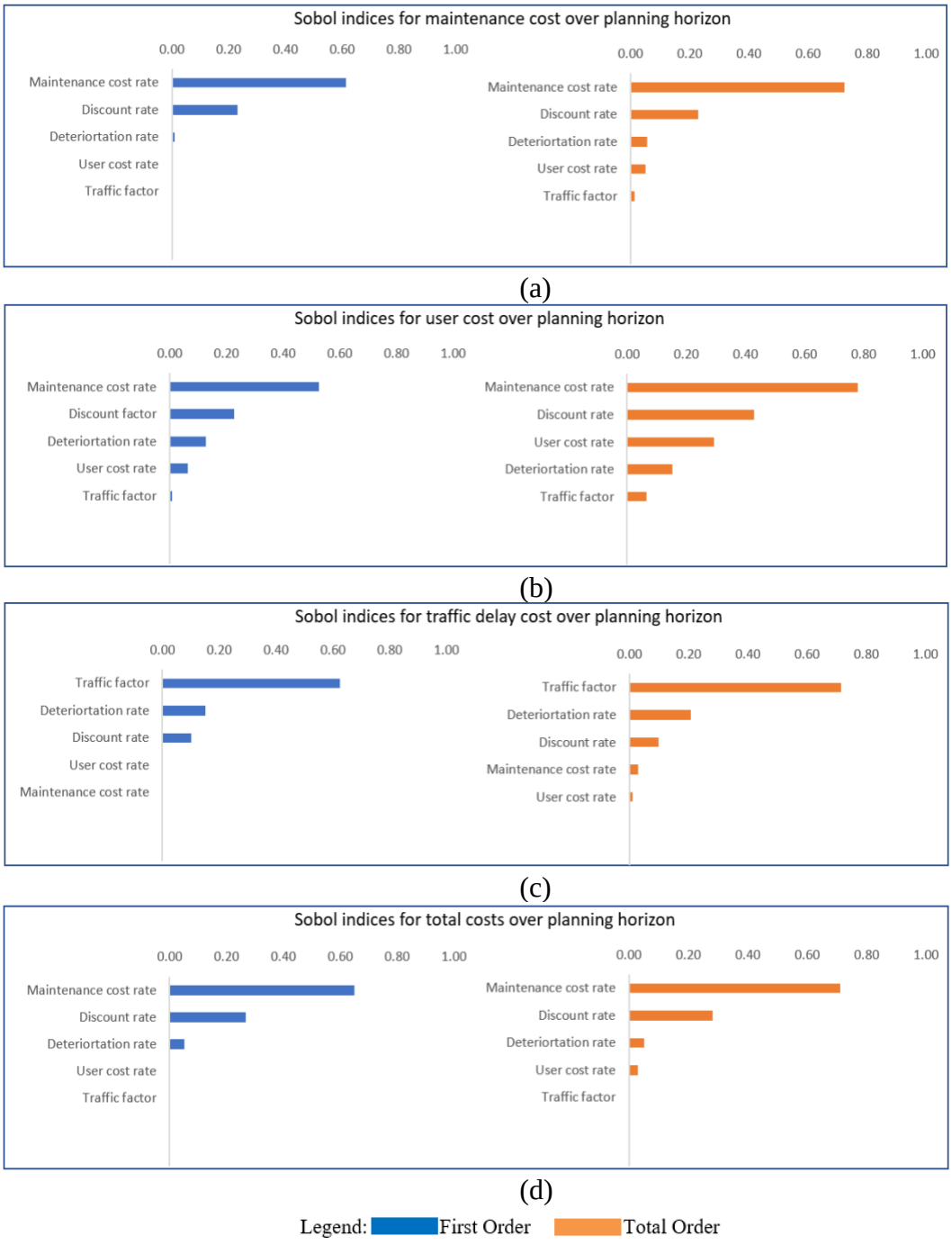


Figure 4.5: First and total order Sobol's sensitivity indices of the model input parameters for the (a) maintenance cost (b) user cost (c) traffic delay cost and (d) total cost over the planning horizon

4.4.2 Global Sensitivity Analysis Using Sobol's Method

The results for Sobol's method, where the sensitivities of each of the four output variables to each of the input parameters are explored simultaneously, are shown in Figure 4.5. In Figure 4.5a, the first order and total order Sobol's sensitivity indices are presented for the maintenance cost over the planning horizon. The first-order indices show that the maintenance cost is most sensitive to the maintenance cost rate as well as the discount rate, suggesting that the rate of change of the value of money significantly affects maintenance cost. Furthermore, it is observed that user cost rate and traffic factor do not independently influence the maintenance cost. However, the total order Sobol's indices show that these two variables are indeed impactful on the maintenance cost. This is because the total order indices capture the variances due to interaction effects among the variables that are not considered in the first-order indices. Similar observations are noted for the user cost over the planning horizon as presented in Figure 4.5b.

In Figure 4.5c, the first order and total order Sobol's sensitivity indices are presented for the traffic delay cost over the planning horizon. Now, we see that the maintenance cost rate is not the most impactful, rather, it is the traffic factor that most impacts the traffic delay cost. Traffic delay cost consists of two components, namely the part that reflects the delays experienced when the improvement action is being implemented, and the second which captures the delays caused by reduced capacity due to continued deterioration of the roads when actions are deferred. As such, it is logical that the traffic factor, a parameter that controls the allowable traffic capacity at any time on the road, be most impactful

on the traffic delay cost. Deterioration rate and discount rate are equally observed to be independently influencing the traffic delay cost; user cost rate and maintenance cost rate are not. The total indices are also quite small compared with other variables thus indicating that the traffic delay cost is less dependent on the maintenance cost rate and user cost rate.

Finally, in Figure 4.5d, the first order and total order Sobol's sensitivity indices are presented for the total cost over the planning horizon. The total cost is the sum of the maintenance cost, user cost, and traffic delay cost. The framework uses total cost as the objective function; therefore, this output cost component is the most important. The results show that for the first-order indices, the user cost rate and traffic factor are the least impactful while the maintenance cost rate is the most impactful followed by the discount rate and then the traffic factor. One reason for this could be because of the way the optimal cost is obtained. Since the maintenance cost constitutes a significant proportion of the total cost and the total cost is used as the criterion to select the optimum policy, as discussed in the case-study model section, the user cost rate has some additive effect in the model but does not independently impact the model outcomes. This observation is critical as it is less intuitive. One would expect that the user cost rate will influence the user cost at least. As such, insights such as this can be used to re-evaluate, and appropriately calibrate, the model parameters thereby underscoring the importance of a variance-based sensitivity analysis as demonstrated in this study Therefore, one can conclude that, unlike the local sensitivity analysis, the global sensitivity analysis can be used to properly extract insights on the behavior of the parameters in a model.

4.5 Conclusion

This study explores and compares the use of a global sensitivity analysis method, called Sobol's method, with the local sensitivity analysis to investigate the impact of input parameter selection in a complex decision support tool for solving a multi-class asset maintenance prioritization and scheduling problem considering traffic impacts to minimize the total cost of improvement investment, user costs and traffic delays due to the downtime resulting from the implementation of the actions over the specified planning horizon. The case study model has five input parameters and four outputs. The results clearly showed the importance of the maintenance cost rate and discount rate but also the role of the other parameters in explaining the variability of total cost. While the results indicated that the optimal policy selected using default values has an objective value that is close to the optimal policy selected using updated parameters, the optimal policy changes more frequently in a more congested network.

This analysis has shown that one must be careful in dealing with the parameters in complex decision support tools as there is a tendency to erroneously underestimate the influence of some parameters on the output when they are considered independently as opposed to their combined effects which may reveal that they are otherwise consequential to the outcome of the model. Examining the variables as demonstrated in this study could be very beneficial as the influence of the selected values of parameters can now be controlled by fixing some factors that have low sensitivity indices in the model thus simplifying the model and reducing their computational requirements. One challenge encountered in this study is the issue of scalability, as is typical for decision support models, which arises when the

modeling frameworks are explored for more complex instances that are characterized by bigger networks for example, rather than toy networks, and the increased computational resources required to obtain decision outputs with the framework.

This study demonstrates to software developers and agencies the importance and value of rigorous sensitivity analysis, both local and global, when selecting or developing a decision support tool. The analysis helps validate the logic and thus, the decisions, understand which parameters require attention, and assist in parameter selection. Sensitivity analysis also provides a structure that agencies can use to compare tools.

What do local and global sensitivity analyses tell agencies about transportation asset management decision support tools? The analyses help identify issues in the implementation of the tools. They recognize which parameters are important individually and in their interactions. They help asset managers set the appropriate values for parameters. They help asset managers to understand the relationships between input variables and parameters and the decision outcomes from the tools. Rigorous local and global sensitivity analysis should be conducted regularly for all new and existing tools.

Chapter 5

INTRODUCTION TO META-MODELS, MACHINE LEARNING AND TRANSPORTATION NETWORK ANALYSIS

5.1 Introduction

Although the proliferation of computing resources, including access to data storage and high-speed computing, and new sources of data, have aided the development of complex optimization methods, optimization methods may perform sub-optimally and the computational cost can be prohibitive when design uncertainties are considered (Negrin, Kripka, & Yepes, 2023). These challenges are exacerbated by evolving problem contexts and the pressure to provide timely decisions. Meta-model development can reduce the complexities of decision models and facilitate less costly evaluation of model outcomes.

A metamodel is a model of another model which captures the latent patterns between the input and output variables (Das, Goerlandt, & Tabri, 2022). In its simplest form, a meta-model's framework first creates vectors of input variables that are needed to evaluate a decision outcome from a physics-based model, followed by a properly designed simulation to obtain corresponding outputs for each input vector. The resulting input-output dataset is then used to develop a regression or interpolation model that can be used to estimate the outcome of the model that otherwise would have required more resources if the physics-based model were used directly (Negrin et al., 2023). In other variants, a metamodel may

combine input-output pairs from real-life data and physics-based data to develop a more sophisticated metamodel (Negrin et al., 2023).

Metamodels have been used in numerous fields, including transportation engineering, to abstract complex optimization models. De Jong, Gunn, and Ben-Akiva (2004) presented a fast, simpler, and approximate meta-model for passenger and freight transportation in Europe based on results from eleven individual transport models. Several runs of each of each of the transport models were performed with variations in each of the inputs, making up the decision scenarios, and the corresponding outcomes from the model run for each scenario were used to develop forecast models that represent the metamodels. Patwary, Huang, and Lo (2021) also proposed an optimization framework for large-scale multimodal traffic simulation based on metamodel simulation. This model uses the gradients of the link flows for the model parameters to improve the metamodel performance. Xie, Qin, Zhi, Dong, and Li (2023) utilized a Kriging model to develop a metamodel for calibrating microscopic traffic simulation, identifying, in the process, the important input parameters that influence model outcomes and their relationships.

Realizing that the solution to the traffic network signal design problem under uncertain Origin-Destination traffic demand requires large computational resources to evaluate the equilibrium flow for different origin-destination (OD) demand distributions, W. Huang, Zhang, Cheng, and Xie (2023) proposed a metamodel framework that approximates the average equilibrium flows. The process for determining equilibrium flows is time-consuming. Incorporating a gradient-based algorithm to capture gradient information of traffic flow for the signal plan avoids bias in the metamodel outcome. In a related work, Purnawan and

Alfathira (2023) simulated the impact of probable landslides using VISSIM microscopic simulations on traffic delays and queues. They used simulated data to generate a metamodel based on a regression analysis that could be used to predict the queue and delay in place of the traffic simulation program, which is expensive to acquire.

Commonly used sampling techniques and model choices in for metamodels in engineering are presented in review studies. Some of the common sampling methods include classical methods such as factorial, central composite, and box Behnken; space-filling methods such as simple grids, latin hypercube, and orthogonal arrays; discriminative sampling methods; sequential methods; importance sampling; and random or human selection methods. Model choices include decision trees, support vector machines, hybrid methods, artificial neural networks, and radial basis functions (G. G. Wang & Shan, 2006). Negrin et al. (2023) also support these choices.

In these studies, metamodels abstract a single complex model into a simpler version to make quicker, less costly decisions. In this research, the idea is extended to a set of models. Here, the metamodel predicts which model is the most suitable for a new scenario, rather than predicting the outcome for that scenario. Machine learning classification techniques are used to build a metamodel using synthesized data representing the attributes of scenarios and the outcomes from a set TAM decision support tools applied to a case study. Machine learning classification techniques are chosen for their simplicity and the clarity of the analysis of the simulated data. The aim is to not overwhelm the users, i.e. asset managers, who are already reluctant to use complex models. The following sections present a brief

discussion of applicable machine learning techniques. This is supported by references to the extensive literature in this field.

5.2 Applicable Machine Learning Techniques

Machine Learning in its broadest sense refers to the science of discovering and analyzing useful patterns and structures from data to facilitate decision making. In other words, machine learning involves a group of methods used to discover patterns from historical data that can be used to make decisions on new, previously unseen, data. Machine learning methods are founded upon techniques in optimization, statistics, algorithms, and biological-inspired systems (Attoh-Okine, 2017; Lasisi, 2019) and their applications are well-established in a variety of fields.

Machine learning methods can be classified into four categories, namely: supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning. Supervised learning requires a labeled dataset i.e. for each observed input set, the corresponding output value is known, unsupervised learning does not, while semi-supervised learning combines both techniques. Reinforcement learning generates the required data as it is being trained. The methods applicable to this research, mainly classification methods, are briefly introduced in the following sections. The methods use the notation shown in Table 5.1.

Table 5.1: Notation used in machine learning algorithms

Variable	Description
β_o	Bias
β	Weighting vector for independent variables
J	Loss function
d	Euclidean distance
E	Entropy
$f^b(x)$	Decision tree for dataset b
G	Gini Index
J	Loss function
M	Margin of separation in SVM
N	Number of classes
n	Number of observations
p	Number of predictors
x_i	Vector of independent variables for observation i
X_j	Vector of feature j
y_i	Response or classification for observation i
Z, f(x)	Function of input variables
y_i	Predicted class for observation i
E	Entropy
G	Gini index
p_i	Proportion of observations in class i for decision tree
ϕ_{ji}	Factor loading of feature j on principal component i

5.2.1 Logistic Regression

Logistic regression is one of the most used, and the most basic, supervised classification algorithms. In logistic regression models, the posterior probability of membership in one of N classes, y, as a function of linear relationship among independent variables, denoted by the vector x, such that the sum of these probabilities of occurrence of y is equal to 1, and y can only assume a value of 0 or 1 (Hastie, Tibshirani, & Friedman, 2017). In its simplest form, when N = 2, the classification problem is binary, but when N is greater than 2, the problem is a multiclass classification.

To develop a logistic regression model, a weighted sum of the input variables plus a bias term, denoted z, is first calculated, then a logistic function is applied to the output z. The logistic (or sigmoid) function converts the weighted sum to the probability of occurrence *y* of the class given the input vector x as shown in Equation 5.1.

$$P(y = 1|x) = \frac{1}{1+ e^{-z}} \quad (5.1)$$

Where $0 \leq P(y = 1|x) \leq 1$

The predicted class is determined as shown in Equation 5.2.

y = 1 if P(y=1|x) ≥ 0.5, and

y= 0 if otherwise. (5.2)

To fit the model to accurately predict the classes, the average of the log loss of the predicted class $\hat{y}_i$ and the actual observed y_i class for n observations is computed as shown in Equation 5.3.

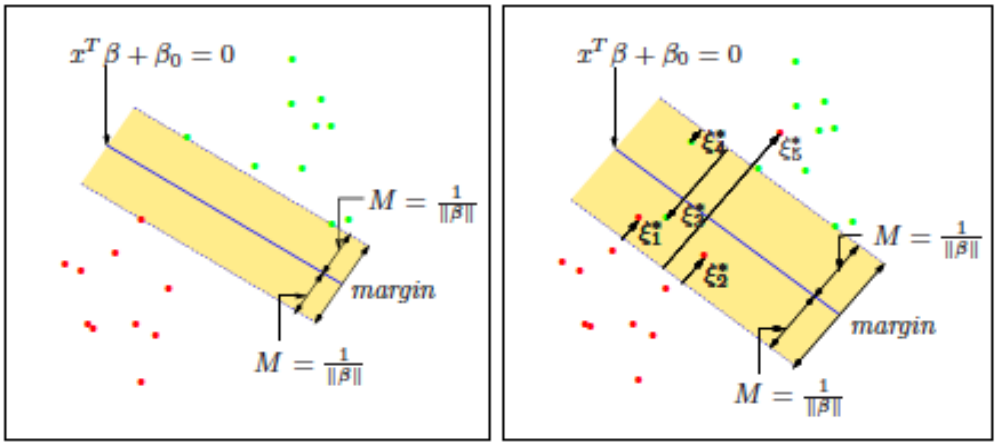
$$J = \frac{1}{n} \sum_i^n [y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)]. \quad (5.3)$$

This is called the loss function, the optimization of which is sought using the gradient descent algorithm (Géron, 2022).

5.2.2 Support Vector Machine (SVM)

The support vector machine (SVM) is a supervised learning algorithm, which unlike logistic regression, is suitable for both regression and classification problems. In SVM, the objective is to define the best decision boundary, called a hyperplane, that maximizes the margin of separation between data points of different classes. Depending on whether the dataset is separable or not, the hyperplane distinctly divides the datasets into the number of classes (for separable

dataset) or otherwise (for non-separable dataset). Once a hyperplane is established from the training dataset, the classes of the testing dataset are assigned based on the side of the hyperplane they fall into **(Hastie et al., 2017)**. Figure 5.1 presents a representation of a support vector machine with two classifications and two variables.



(a) (b)

Figure 5.1: Representation of support vector machine (Hastie et al., 2017)

Figure 5.1(a) illustrates a hyperplane for a separable dataset. The hyperplane is defined by the dashed solid lines, while the dashed lines define the maximum margin of width $2M = \frac{2}{||\beta||}$ where M is some units distance of the decision boundary from the dashed lines. Figure 5.1(b), on the other hand, illustrates a hyperplane for a non-separable dataset. Again, the meaning of the dashed and solid lines remains the same, but the label ξ_j^* identify points that fall on

the wrong side of the margin by a magnitude of $\xi_j' = M\xi_j$ where $\xi_j^* = 0$ for points on the correct side of the hyperplane. The goal is to maximize the margin M subject to a total budget $\sum \xi_i \leq \text{constant value}$, which implies that $\sum \xi_j^*$ is the total distance of points on the wrong side of their margin.

To train an SVM, the hyperplane is defined for a separable dataset Figure 5.1(a) as (Hastie et al., 2017):

$$\{x: f(x) = x^T\beta + \beta_o = 0\},$$

where x is the feature vector, β is a unit vector: $||\beta|| = 1$, i.e. the norm of the weight vector, and β_o is the bias term. Given the margin $2M = \frac{2}{||\beta||}$ (or $M = \frac{1}{||\beta||}$), an optimization problem to maximize the margin is formulated as follows:

$$\max_{\beta,\beta_o,||\beta||=1} M$$

$$\text{subject to } y_i(x_i^T\beta + \beta_o) \geq 1, \text{for } i = 1, 2 \ldots n,$$

which is equivalent to

$$\min_{\beta,\beta_o} ||\beta|| \text{ , since M is inversely proportional to } ||\beta||,$$

$$\text{subject to } y_i(x_i^T\beta + \beta_o) \geq 1, \text{for } i = 1, 2 \ldots n.$$

This can be expressed as

$$\min_{\beta,\beta_o} \frac{1}{2}||\beta||^2$$

$$\text{subject to } y_i(x_i^T\beta + \beta_o) \geq 1.$$

For non-separable dataset Figure 5.1b, the optimization problem becomes (Hastie et al., 2017):

$$\min_{\beta,\beta_o} \frac{1}{2}||\beta||^2 + C\sum_{i=1}^{n} \xi_i$$

$$\text{subject to } \xi_i \geq 0,$$

$$y_i(x_i^T\beta + \beta_o) \geq 1 - \xi_i \forall_i,$$

where C is the tradeoff between the margin and the misclassification error and ξ_i is the extent to which the prediction $f(x)$ is on the wrong side of the margin.

5.2.3 *k*-Nearest Neighbor (KNN)

k-nearest neighbor **(**KNN) is also a supervised learning algorithm that determines the class of a given data point, x_0, based on the classes of the closest k data points $x_r, r = 1, 2 \ldots, k$. The most frequently occurring class is assigned to the data point, and when there is a tie between more than one class, the selection is done randomly. KNN does not require a model to be fit, however, a distance measure must be specified. The most common distance measure is Euclidean distance d, assuming the features are real-valued:

$d = \sqrt{\sum_{i=1}^{n}(x_i - x_0)^2}$.

Other distance measures are (Hastie et al., 2017; Lasisi, 2019).

Manhattan Distance $d = \sum_{i=1}^{n}|x_i - x_0|$ and

Minkowski Distance $d = (\sum_{i=1}^{n}|x_i - x_0|^p)^{1/p}$

5.2.4 Decision Tree

A decision tree is a diagrammatic representation of data where each node represents a feature or attribute, and a decision rule is represented by a branch. The leaves of the tree indicate the outcome of the label which could either be categorical or continuous (Lasisi, 2019; Marsland, 2011). A decision tree is constructed by recursively partitioning the feature space of the training set with the objective of finding a set of decision rules that distinctly partition the feature space to provide an informative and robust hierarchical classification model (Myles, Feudale, Liu,

Woody, & Brown, 2004). In other words, building a decision tree involves proposing many possible data cuts and then choosing best cuts based on simultaneous competing criteria of predictive power, cross-validation strength, and interaction with other chosen cuts (Mount & Zumel, 2019). For classification problems, the metrics for splitting are the Gini Index and Information Gain (or Entropy). The Gini Index is computed at every split instance as:

$$G = 1 - \sum_{i=1}^{K} p_i^2$$

where K is the number of classes, p_i is the proportion of observations in class i. A lower G value indicates higher node purity, so the data is split by minimizing the G value at each node.

Entropy, on the other hand, is computed as:

$$E = -\sum_{i=1}^{K} p_i \log p_i.$$

Like G, the goal is to minimize E at each node (Gareth, Daniela, Trevor, & Robert, 2013). It is typical to stop splitting when the specified maximum tree depth or minimum samples at each node is achieved or when the data points within a node are all in the same class.

5.2.5 Random Forest

Random forest is a supervised learning algorithm that is built upon ensembles of decision trees. In other words, it combines the predictions from several weak learners, i.e. decision trees, and outputs a more accurate result. It leverages the concept of a bootstrap sampling technique called bagging (bootstrap aggregating) to train multiple decision trees. This involves randomly selecting n observations from the dataset B times to obtain B different bootstrapped sets, which

are then used to train independent decision trees $f^1(x), f^2(x), \ldots, f^B(x)$. After training, the predicted response for a new sample is the average prediction

$$f_{bag}(x) = \frac{1}{B} \sum_{b=1}^{B} f^b(x)$$

This prediction minimizes the variance between the weak learners. In doing this, to ensure that the weak learners are not correlated, every time a split is done in a tree, a random sample of m predictors, such that $m \approx \sqrt{p}$, is selected from the pool of all predictors p and used in for splitting. This way, on average, $(p - m)/p$ of the splits will not consider the strong predictor, giving more chance to other predictors (Gareth et al., 2013).

In the case of classification, the predicted response of the random forest model is computed by majority vote among the predicted classes from the weak learners. Just like decision trees, splitting may be stopped when the maximum tree depth or minimum samples per leaf node is attained.

5.2.6 Cluster Analysis

Cluster Analysis is an unsupervised learning technique that involves grouping and assigning labels to observations based on similarities. The similarity is often measured by a distance metric, such as Euclidean distance, Manhattan distance, or Minkowski distance, which are presented in Section 5.2.3. The goal of clustering is to maximize the inter-cluster distance and minimize the intra-cluster distance between observations i.e., to ensure that data is split into groups such that members of a cluster are more similar to each other and more different from those of other clusters.

One of the most common cluster analysis techniques is K-Means Clustering. It involves randomly defining initial cluster centroids k. Then the data points are assigned to the nearest centroid and the average of the data points in each cluster is obtained as the updated centroid for that cluster. This process is repeated until the total within-cluster variance: $\sum_{i=1}^{k} \sum_{c_i} ||x - \mu_i||^2$ is minimized (Gareth et al., 2013). One limitation of K-Means is that the k must be specified.

Another common cluster analysis technique is Hierarchical Clustering. Unlike K-means clustering, hierarchical clustering does not require that the number of clusters be specified before the analysis. Instead, they require the user to specify a measure of dissimilarity between (disjoint) groups of observations, based on the pairwise dissimilarities among the observations in the two groups (Lasisi, 2019). As a visualization tool, hierarchical clustering produces tree-like representations, called dendrograms, in which the clusters at each level of the tree are created by merging clusters at the next lower level. At the lowest level, each cluster contains a single observation and at the highest level, there is only one cluster containing all the data. Each level of the tree represents a particular grouping of data into disjoint clusters of observations. The entire tree represents an ordered sequence of such groupings (Lasisi, 2019).

5.2.7 Principal Components Analysis (PCA)

Principal components analysis (PCA), also an unsupervised technique, is a dimensionality reduction technique. The objective is to capture a significant proportion of the variance in a muti-dimensional dataset with fewer new variables called principal components where a principal component is a linear combination

of a subset of the actual variables that explains the maximum variance in the dataset. It is also an unsupervised learning algorithm. Given a dataset of p dimensions (i.e. number of features), the data is thought of as being points in a p-dimensional space. The axes of the p-dimensional space are rotated along lines that maximize the variation in the data. The new axes are then used to project the p-dimensional data onto k dimensions, where k < p, such that the k-dimensional projection retains the maximum possible variance in p-dimensional data.

To implement PCA on a normalized feature matrix x: $x = x_{1,}\, x_{2,} \ldots, x_{p,}$ of n number of observations, the principal component is defined as the linear combination of the original features:

$$z_i = \phi_{1i}x_1 + \phi_{2i}x_2 + \ldots + \phi_{pi}x_p$$

where z_i is the i-th principal component, ϕ_{ji} is the loading of the j-th feature on the i-th principal component, and the loadings are constrained so that $\sum_{j=1}^{p} \phi_{ji}^2 = 1$ to prevent outrageously large loadings. This is called the normalization constraint. Since the principal components maximizes the variance in the data, the optimization problem is solved:

$$\text{maximize } \frac{1}{n}\sum_{i=1}^{n}\left(\sum_{j=1}^{p}\phi_{j1}x_{ij}\right)^2$$

$$\text{subject to } \sum_{j=1}^{p}\phi_{ji}^2 = 1$$

where x_{ij} is the value of the j-th feature for the i-th observation.

The outcome is the first loading vector

$$\phi_1 = \left(\phi_{11} + \phi_{21} + \ldots + \phi_{p1}\right)^T$$

which is the first principal component. Successive principal components are computed by solving similar optimization problem ensuring that the new principal

component ϕ_k is orthogonal to the previous ϕ_l, essentially introducing a second constraint called the orthogonality constraint: ${\phi_k}^T\phi_l = 0$ for all $l < k$. This optimization can be solved by calculating the ordered sequence of the eigenvectors of the matrix x^Tx and the corresponding eigenvalues, where the eigenvectors are the direction of the principal components and eigenvalues are the variances captured by each of them (Gareth et al., 2013).

5.2.8 Summary of ML Methods

Table 5.2 summarizes the methods discussed. The methods are composed of five supervised and two unsupervised learning techniques. The five supervised learning methods are trained upon labeled data and are suitable for predicting the class of a new data point. Clustering methods use the similarities between data points to establish latent groups in the dataset. Principal component analysis transforms higher dimensional data to smaller dimensional data to enhance predictions. Both clustering methods and PCA can be used as preprocessing step before the implementation of the classification methods. The decision on whichever method to use requires careful consideration of some factors that are briefly discussed in the next section.

Table 5.2: Summary of applicable machine learning methods

Method	Type of Learning	Concept	Source
Logistic Regression	Supervised	Models the posterior probability of membership in a class	Hastie et al., 2017
Support Vector Machine (SVM)	Supervised	Defines a decision boundary to maximize the separation between data points	Hastie et al., 2017
k-Nearest Neighbor	Supervised	Class is determined on class of the closest data points	Hastie et al., 2017
Decision Tree	Supervised	Partitions the feature space to classify data	Myles et al., 2004
Random Forest	Supervised	Ensembles of decision trees	Gareth et al., 2013
Cluster Analysis - k-Means - Hierarchical Clustering	Unsupervised	Maximize the inter-cluster distance and minimize the intra-cluster distance between observations	Gareth et al., 2013 Lasisi, 2019
Principal Components Analysis (PCA)	Unsupervised	Dimensionality reduction	Gareth et al., 2013

5.2.9 Machine Learning Model Development Considerations

The development of a machine learning model requires careful consideration of the factors that affect the selection of models, as well as the outcomes of the model. Some of these are briefly discussed here.

5.2.9.1 Problem Characteristics

The type of problem influences the algorithm selected, as well as the outcomes. Whether a classification algorithm, clustering algorithm or regression algorithm is utilized depends in part on the nature of the problem. For example, using a regression algorithm for a classification problem may not achieve optimal model outcomes.

5.2.9.2 Quality of Dataset

The quality of data is one of the most important factors that influences the performance of the model. Data quality is affected by missing data points, outliers, as well as disparities in the order of magnitudes of the features. So, it is important to ensure that missing data and outliers are handled. Also, normalization or standardization of features is helpful to ensure that all features are of similar orders of magnitude. Imbalance or covariate shift phenomenon in the data also affects the quality of the model (Balogun & Attoh-Okine, 2021) and appropriate techniques must be adopted to address them. Also, unimportant features in the dataset affect model performance, and feature engineering techniques can be applied to identify important features.

5.2.9.3 Model Complexity and Computational Requirements

Complex models potentially lead to more accurate model predictions, but they usually require large datasets and excessive computational resources. So, if these resources are not available, it may be better to adopt simpler models.

5.2.9.4 Hyperparameter Tuning

Hyperparameters are quantities that need to be prescribed, rather than learned, for configuring the machine learning algorithms before training them. The values set for the hyperparameters can mar the performance of the model and must be carefully selected. The hyperparameters vary from one algorithm to another, with some of them listed as follows (Géron, 2022; Mount & Zumel, 2019):

- Logistic regression - the regularization type (Lasso or Ridge), regularization strength, and choice of optimization solver.
- SVM - regularization parameter and kernel choice.
- KNN - number of neighbors, distance metric, and weight choice.
- Decision trees - maximum depth of tree, split criterion, and minimum samples per leaf.
- Random forests - number of trees, maximum features per split and maximum depth of trees.
- Cluster analysis - number of clusters, distance metric, and initialization method.
- Hierarchical clustering - linkage choice and distance metric. PCA - number of components.

Given the importance of hyperparameters, these parameters must be tuned to achieve the optimal model performance. Different tuning strategies exist including, but not limited to, grid search and random search. In this research, grid search is adopted.

5.2.9.5 Model Evaluation

Appropriate evaluation metrics must be used to assess the performance of models to avoid misinterpretations. Usually, for regression problems, mean squared

error (MSE) or root mean squared error (MSE), R-squared, and mean absolute error (MAE) are the commonly used metrics. For classification, accuracy, precision, recall, F1-score or harmonic mean of precision and recall, and ROC-AUC (area under the receiver operating characteristic curve) are the commonly used metrics. It is also a common practice to access the model for overfitting, a phenomenon where the model learns the data too well and then fails to generalize to new data (Géron, 2022; Mount & Zumel, 2019).

5.3 Transportation Network Analysis

5.3.1 Overview

Network analysis is a group of techniques that uses the principles of graph theory to study the interactions among entities such as persons, organizations, physical objects, and systems. These entities are referred to as nodes or vertices while the connections between them are called edges or links. Thus, a network, also known as graph, is made up of a set of nodes and edges, that enables the flows of information, objects or resources through an n-dimensional space (Taylor, 2017). Network science has applications in diverse domains including but not limited to social sciences, information and communication sciences, health sciences, and transportation.

In transportation and infrastructure systems, network analysis has been applied in numerous studies. Aderinlewo (2008) assessed the system behavior and component interactions of transportation infrastructure system by studying the impact of targeted and random disruptions in the system on its performance.

Háznagy, Fi, London, and Nemeth (2015) asserted that the patterns of road networks influence the performance of traffic, travel behavior, and traffic safety, thus a thorough understanding of the properties of different road network patterns can help in the improvement of road systems. Háznagy et al. (2015) studied complex network analysis of urban public transportation systems of five different cities with the goal of identifying significant similarities and differences in the transportation networks that could inform decision-making. Xu, Chen, Jansuwan, Yang, and Ryu (2018) used network-based measures to systematically characterize redundancy in transportation networks. Serdar, Koç, and Al-Ghamdi (2022) described the application of graph theory as a viable method for studying urban transportation networks resilience. Promsuwan, Nakayama, Yamaguchi, and Kobayashi (2023) used the closeness and betweenness centrality measures, which are important properties of networks, to identify and analyze critical stations and sections in a rail network. Ahmed, Kays, and Sadri (2023) implemented, on a real-world transportation network, a framework that identifies critical links in a road network based on the network topology as well as the impacts of interventions conducted on the segments (e.g. links) on the overall performance of the network. Evidently, the structural properties of networks hold useful information that facilitates the understanding of transportation and infrastructure systems and there are established metrics that can be used to extract this information.

5.3.2 Network Measures

Network metrics that assess the structural properties of networks can be classified into three depending on the level of information desired. These are node-

level or centrality metrics which measure the relative position of a node in a network; group-level metrics which identify group patterns among nodes in a network; and network-level metrics which are calculated on the whole network and provide indicators of the network structure as a whole (Valente, 2010). Another classification divides the metrics into three categories namely; (1) local measures which focus on the information at the node level (2) global measures which are computed using the entire network structure, and (3) mixed metrics which are computed using measures of the nodes as well the topology information from the connections that results from their direct and indirect proximity (Shi, Yan, Guo, & Ai, 2020). Other classification may exist, but network-level measures are of interest in this study since they are aggregate measures of the network that facilitate global analysis by providing a comprehensive understanding of the overall structure and characteristics of a network. In the following sections, some global measures are discussed. Table 5.3 presents the notations that are used in the discussing of these measures.

Table 5.3: Notation used to compute network properties

Notation	Description
G	an idealized graph of a network
A	adjacency matrix of the network
a_{ij}	Element (i, j) of the adjacency matrix
k_i	degree centrality i.e. the number of edges connected to a node i
$< k >$ or $d(G)$	average degree centrality for the network
d_{ij}	shortest distance between two points i and j
CI_i	closeness centrality i.e. measures the closeness of node i to other nodes in the network.
n_{jk}	number of shortest paths connecting nodes j and k
$n_{jk}(\propto)$	number of shortest paths between nodes j and k that contain edge $\propto$
$n_{jk}(i)$	number of shortest paths connecting j and k passing through i
L	average path length of the network
c_i	local clustering coefficient of network
c_c	average local clustering coefficient
$\epsilon_{i,j}$	efficiency between two nodes i and j
E(G)	global efficiency of a network
G_i	subnetwork of neighboring nodes around nodes i
e_i	number of edges in a subnetwork G_i
n_d	density of a network

5.3.2.1 Centrality

Centrality is one of the most fundamental properties of networks that describes the importance of nodes and edges in a network. One important application of centrality is to identify critical nodes in the network that are vulnerable to disruptions. By identifying such critical nodes, transportation planners can prioritize investments in redundant infrastructure or alternate routes to mitigate the impact of disruptions, optimize routing (i.e., minimizing travel time and distance) by prioritizing routes that connect important hubs with high degree centrality and study the trends and patterns in the development of transportation networks over time (Stamos, 2023). Several measures of centrality, some of which have been discussed by Stamos (2023), are well documented in literature. However,

there are three most common types of centrality measures that are assessed when analyzing a network. These are: degree centrality, closeness centrality, and betweenness centrality.

Degree centrality represents the number of edges connected to a node. Its measure is based on whether the network is directed or undirected. In directed networks, the edges are oriented in specified directions, however, for undirected networks, each edge between two nodes runs both opposite directions (Aderinlewo, 2008). For undirected network, degree centrality is measured as:

$$k_i = \sum_{j \in N} a_{ij}$$

where a_{ij} is the adjacency matrix A_{ij} of the network (Aderinlewo, 2008; Stamos, 2023).

The adjacency matrix is the square matrix that represents a graph or network by encoding the connections between nodes. In the context of degree centrality, the adjacency matrix is typically binary, where each element (i, j) in the matrix represents whether there is an edge connecting node i to node j in such a way that when there is an edge between nodes i and j, the element (i, j) of the adjacency matrix is 1 and when there is no edge between nodes i and j, the element (i, j) is 0 (Stamos, 2023).

For directed networks, the degree centrality has two components, the number of outgoing edges from the nodes,

$$k^{out} = \sum_{j \in N} a_{ij} \text{ and } k^{in} = \sum_{j \in N} a_{ij}.$$

The sum of these two components give the degree centrality (Aderinlewo, 2008; Stamos, 2023).

In application, nodes with the higher degree centrality are more central in a network. However, it is worth noting that while degree centrality is a good measure of the total connections a node has, it may not necessarily indicate the importance of a node in connecting others or how central it is to the main group (Golbeck, 2013). This is especially the case in transportation systems, according to (Stamos, 2023), because degree centrality seems to be independent of traffic capacity which is usually the fundamental variable assessed in transportation network problems. Stamos (2023) argue that while degree centrality in some sense could identify nodes that have higher importance primarily because of the number of connections they have, such importance is limited because it does not really capture the amount of traffic loads through the nodes.

Closeness centrality is a measure of the nearness of a node to all other nodes in the network. Numerically, it is defined as the inverse sum of the closest distances from a node under consideration of all nodes in a network. Closeness centrality is computed as:

$$\mathrm{CI_i} = \frac{1}{\sum_j \mathrm{d_{ij}}}$$

where d_{ij} is the shortest distance between nodes i and j (Stamos, 2023).

In application, nodes that have higher values of closeness centrality measures are more central in the network and are closer to most of the nodes in the network (Golbeck, 2013). As such, because of their central position in reference to all other nodes in the network, it is easier to reach other nodes in the network thus making them good candidates for the location of hubs in the network (Stamos, 2023).

Betweenness centrality is a measure of the number of times a node lies in the shortest paths connecting all other pairs of nodes in the network (Valente, 2010). In other words, it measures the importance of a node to all the shortest paths through the network (Golbeck, 2013). To compute betweenness for a node i, we select a pair of nodes and find all the shortest paths between those nodes. Then we compute the fraction of those shortest paths that include node i. If there were five shortest paths between a pair of nodes, and three of them went through node i, then the fraction would be 3÷5=0.6. This process is repeated for every pair of nodes in the network. The computed fractions are then added up, and this is the betweenness centrality for node i (Golbeck, 2013). In the calculation of the betweenness, the node i cannot be at the end of any shortest paths (Aderinlewo, 2008; Dueñas-Osorio, 2005). Mathematically, betweenness centrality can be computed as:

$$b_i = \frac{1}{(N-1)(N-2)} \sum_{\substack{i,j \in N \\ i \neq j}} \frac{n_{jk}(i)}{n_{jk}},$$

where n_{jk} is the number of shortest paths connecting j and k and $n_{jk}(i)$ is the number of shortest paths connecting j and k passing through i (Aderinlewo, 2008).

This betweenness property of nodes can be extended to edges too. This way, it measures the importance of a specific edge in facilitating the flow or connectivity between other pairs of nodes. Edge betweenness centrality of an edge is defined as the number of shortest paths between pairs of nodes that passes through that edge, and it can be expressed mathematically as:

$$b_{ij} = \frac{1}{(N-1)(N-2)} \sum_{\substack{j,k=1\ldots N; \\ j \neq k \neq i}} \frac{n_{jk}(\propto)}{n_{jk}},$$

where $n_{jk}(\propto)$ is the number of shortest paths between nodes j and k that contain edge $\propto$ while other terms remain the same as for node betweenness (Aderinlewo, 2008).

In application, high node betweenness or edge betweenness centrality indicates that the node or edge is crucial for maintaining flow within the network. Thus, betweenness centrality is one of the most used measures of centrality (Golbeck, 2013).

Centrality measures are local-level measures as they are assessed on the nodes or edges in the network. However, they may be transformed into single-value measures that can reflect global properties of the network. For example, average degree centrality has been used as a single-value global measure that captures the individual degree centrality of all the nodes. Average degree centrality is simply the average of all node degree centralities. It is expressed as (Aderinlewo, 2008):

$$< k > = d(G) = \frac{1}{|N|} \sum_{v \in N} k_i$$

Similarly, node betweenness centrality, edge betweenness centrality, and closeness centrality, could be respectively represented on a global scale as average node betweenness centrality, average edge betweenness centrality, and average closeness centrality. Just like the average degree centrality that averages the individual node degrees, the average node betweenness, average edge betweenness, and average closeness centrality measures would each provide a single global value that characterizes the entire network's structure in terms of how well-connected or cohesive it is. It is important to mention that there is no known application of these concepts (i.e. averaged centrality measures, excluding averaged degree centrality) in this manner that the author is aware of.

5.3.2.2 Size and Density

Both size and density are network level measures that can facilitate global analyses. Size is characterized by the number of nodes in a network. Although not the most interesting feature, size is the primary network indicator (Valente, 2010) of a network. For one, it may suggest complexity as larger networks are most likely more complex. Density is the number of edges in the network expressed as a fraction of the total number of possible edges. For an undirected network, the density can be expressed as:

$$n_d = \frac{2N_i}{N(N-1)} \text{ for } 0 \leq N_d \leq 1$$

where N is the number of nodes, N_i is the total number of connected nodes in the network, while N(N-1)/2 is the maximum number of possible edges in the networks (Aderinlewo, 2008). A maximum value of 1 corresponds to a dense (or fully connected) network while a minimum value of 0 corresponds to a sparsely connected network.

Density is an important attribute of a network and should always be included as a covariate in analyses testing the effect of other structural properties (Valente, 2010). For example, as density increases, the average path length decreases, because high-density levels provide many paths along which nodes can be connected (Valente, 2010). In application, this could mean that there are a lot of alternatives, perhaps also redundant, paths when traversing between two points in the network thus facilitating easy and timely access to most destinations within the network. Conversely, it could also imply that the network is heavily congested when there are less redundant paths among all the available paths between two

points in the dense network thus leading to traffic jams, delays, and decreased efficiency of the network.

Exploring the importance of density further, an interesting study on network density reveals that density values above 50% indicate networks that have many redundant paths between nodes and do not contain substantial structural information about the network. Hence, deleting links, or even nodes, in such networks will have little effect on the overall network properties and it is desirable to prune such networks accordingly (Valente, 2010).

5.3.2.3 Diameter and Average Path Length

These are two fundamental properties of a network that facilitate global analysis. The diameter is the length of the longest path in the network. In other words, it is the maximum distance (i.e., number of edges) between nodes in the network. On the other hand, the average path length (APL) is the average of the distances between all pairs of nodes in a network, and it is sometimes referred to as the characteristics path length (Valente, 2010). It is expressed mathematically as:

$$L = \frac{1}{N(N-1)} \sum_{i \neq j} d_{ij}$$

where N is the number of nodes in the network, and d_{ij} is the shortest path length between node i and node j (Umaisara Rashid & Chan, 2023). In application, smaller average path length implies that, on average, traveling between any two points in the network is quicker and vice versa.

5.3.2.4 Clustering Coefficient

Network clustering is a measure of the degree of cohesiveness in a network. It is the tendency of the nodes in a network to form cliques – a group of nodes that have exclusively similar attributes (Aderinlewo, 2008). A network with high clustering indicates that nodes are connected in dense pockets of interconnectivity, whereas one with low clustering has few pockets of interconnectivity. Clustering provides an index of the degree of structure in the network. It is a measure that facilitates global analysis (Valente, 2010) and can be assessed either as a global clustering coefficient or an average local clustering coefficient. To compute the average local clustering coefficient a network *G*, the local clustering coefficient is first computed for each node as the ratio of the actual number of edges e_i in the subnetwork G_i of the neighbors of the node to the maximum possible number of edges in the network N(N-1)/2. This is represented:

$$c_i = \frac{2e_i}{N(N-1)}.$$

Then, the average local clustering coefficient is computed as (Aderinlewo, 2008):

$$c_c = \frac{1}{N}\sum_{i \in N} c_i.$$

The global clustering coefficient is the number of triangles found in a set of nodes divided by the total number of connected triplets found in this given set. A connected triplet corresponds to three nodes connected by at least two edges. Triangles are cliques of three nodes, in which each node is directly connected to the two others. Therefore, the intuition behind the global clustering coefficient is to measure the density of connected triplets that form triangles in a graph, which indicates how many edges are clustered together (Dubitzky, Wolkenhauer, Cho, &

Yokota, 2013). Another term for global clustering coefficient is transitivity. Transitivity in a network exists when there is the following combination of links among three nodes: if A → B, and B → C, then A → C (Valente, 2010). Valente (2010) provides all possible configurations of triangles that could be formed from three nodes.

5.3.2.5 Assortativity

Assortativity in networks refers to the tendency of nodes to be connected to similar nodes. In other words, it measures the preference of nodes to attach to others with similar attributes or degrees. The assortativity coefficient is a numerical measure quantifying this tendency and is calculated using the Pearson correlation coefficient between the degrees of connected nodes. A positive assortativity coefficient indicates that nodes with similar degrees are more likely to connect, while a negative coefficient suggests a preference for nodes with dissimilar degrees to connect (Noldus & Van Mieghem, 2015). Assortativity is a crucial concept in network science as it provides insights into the structure and organization of networks. Highly assortative networks are characterized by the formation of clusters of nodes with similar properties, fostering robustness and resilience. Assortativity facilitates global analysis.

5.3.2.6 Efficiency and Global Efficiency

Efficiency is a measure of the ease of traversing from one node to another node in a network. The efficiency between two nodes i and j is defined as

$$\epsilon_{ij} = \frac{1}{d_{ij}} \text{ for all } i \neq j$$

where d is the distance between the two nodes, measured as the minimum number of edges between them, while the global efficiency on the other hand is the average efficiency over all $i \neq j$ nodes (Ek, VerSchneider, & Narayan, 2015). Global efficiency on the other hand is a measure of how easy it is to move through the network. It is based on the average shortest path length between any two pairs of nodes (Henry, Furno, & Faouzi, 2021) and is particularly accurate for reflecting the network performance before and after disruptions (Aderinlewo, 2008). The global efficiency of the network is extremely accurate in reflecting the changes in connectivity reliability of complex networks before and after internal failures and external attacks (Ren, Zhang, & Yu, 2023). For a network or graph G, the global efficiency can be expressed as (Aderinlewo, 2008):

$$E(G) = \frac{1}{N(N-1)} \sum_{i \neq j} \epsilon_{ij}$$

Numerous studies have used global efficiency to evaluate the performance of transportation networks (Gong, Lv, Gao, & Wang, 2023; Haritha & Anjaneyulu, 2023; Promsuwan et al., 2023; Szell, Mimar, Perlman, Ghoshal, & Sinatra, 2022).

5.3.2.7 Travel Time Index

Travel time index (TTI) is not a typical measure found in regular network analysis but it is a relevant measure for assessing access for transportation networks. TTI is simply a measure of traffic congestion on a transportation network. It is the ratio of the travel time for the network during peak period to the free-flow travel time for the network (Levinson & Lomax, 1996). The peak period travel time is the time it takes to travel from an origin node in a network to a destination node in the network, typically through the shortest path, during the peak

period. The free flow travel time, on the other hand, is the time it takes to travel between origin and destination, typically through the shortest path, assuming no congestion on the network (Subrat Mahapatra & Sadabadi, 2015).

Travel time index is expressed as:

$$\text{TTI} = \frac{\text{Travel time for the network during peak period}}{\text{Free flow travel time for the network}}$$

Once the TTI value is computed for a network, the network can be characterized based on the congestion level. Several characterization thresholds exist. The Maryland Department of Transportation (MDOT)'s characterization is as follows: 0 < TTI < 1.15 as uncongested; 1.15 <= TTI < 1.30 as moderately congested; 1.3 < TTI < 2.0 as moderately congested and TTI >= 2.0 as severely congested (Subrat Mahapatra & Sadabadi, 2015).

Chapter 6

A META-MODEL FRAMEWORK FOR MATCHING DECISION SUPPORT TOOLS TO TRANSPORTATION ASSET MANAGEMENT DECISION SCENARIOS

6.1 Introduction

At the core of planning for the maintenance and rehabilitation of highway infrastructure are the management systems, including pavement and bridge management systems, that are used to make decisions about the cost and timing of treatment interventions. This study refers to these systems as decision-support tools.

The importance of decision support tools in transportation asset management (TAM) cannot be over-emphasized. This is due to the growing complexities in the requirements for infrastructure systems, which unfortunately cannot entirely be supported by the limited resources available to highway agencies. This reality begs for constant innovative approaches to the management of the systems. However, this has led to the continued proliferation of decision support tools, solving similar problems that are not used by highway agencies. Chen and Bai (2019) after reviewing over 337 articles on the application of optimization to infrastructure management asserted that although most of the algorithms encountered were different, the problems explored were mostly similar and that while most of the methods have demonstrated great results, the models mostly

present a customized approach (i.e., usually one method is discussed) to solving a specific problem, thus making it difficult to have a comprehensive knowledge of the broad application of optimization methods in TAM. In addition, the disparities in the practices adopted by different transportation agencies have also contributed to highway agencies' widespread and somewhat inconsistent adoption of asset management principles. Despite the potential opportunities realized from the use of these models, transportation agencies express skepticism due to the lack of transparency, and obscure nuances in the application of more complex models (Z. Wang & Pyle, 2019).

To mitigate this challenge, efforts should be made to maximize the benefits of these numerous models. One pilot example of such an effort is the Federal Highway Administration (FHWA)'s recent development of a new study area called Analysis, Modeling, and Simulation (AMS) to support investment decisions for transportation systems. The focus of this new area is to assess and quantify the benefits of decision support systems, the data sources, and alternative strategies; build AMS tools for researchers and practitioners; facilitate collaboration between highway industry partners to adopt the decision tools; and provide guidance for the implementation of the tools (FHWA, 2023a).

One example of a recent project in the AMS study area is the development of analysis, model, and simulation tools for connected and automated vehicle applications (Z. Huang et al., 2021). The study was aimed at synthesizing the several models that have been developed for connected and automated vehicles (CAVs) by different researchers based on diverse assumptions into a consistent set of models that use the best available data and the most accurate idealization of

CAVs drivers' behaviors that ultimately result in the realistic predictions of the impacts of CAVs. Case studies using the most prominent models on practicable scenarios and real-world transportation networks were developed to understand the benefits of using the models. A significant part of the methodology in the study is a sensitivity analysis of model outcomes on simulated scenarios.

Some other efforts of the AMS study area have focused on the enhancement of the state of the practice. An ongoing project on the development of a transportation system simulation manual acknowledges the need for a standardized guidance for the development and application of simulation models in transportation systems and proposes to develop one that, among other objectives, provides current and recommended practices and requirements for model scoping, selection, calibration and validation, and identifies important parameters to be used in the calibration and validation of traffic simulation models (FHWA, 2023b).

Although the AMS efforts are currently limited to the connected and automated vehicles and traffic simulation area, this initiative underscores the importance of frameworks for verifying, validating and simplifying decision models in transportation asset management systems. In this research, a meta-model framework is proposed for the area of transportation asset management that explores a set of models representing different levels of analytical complexity and guides the users to the most plausible or suitable model for a given context.

6.2 Overview of the Framework

Consider a portfolio of N decision support tools available to solve the same infrastructure asset management problem. Since highway network-level decisions

often require multiple iterations of considerations of different scenarios and strategies, using each of the N tools during every iteration may be prohibitive and can be discouraging. Understandably, the tools may perform relatively better than one another in different scenarios, thus, systematically selecting the tool to use during every scenario may be very helpful to reduce the efforts and time, that would have otherwise been expended if all the tools were to be explored. So, assuming a decision maker desires to use only one tool that balances the tradeoffs between computational effort and outcomes with high confidence, we define a higher-level metamodel based upon the N decision models (in this case, N=3 using our case study) that can be used for this purpose.

Here, the three different highway network lifecycle cost estimate models solve the same problem, but are of varying levels of complexity - simple, moderately complex, and complex. In these models, complexity is used to represent the computational effort required to determine the maintenance policy. The simple model requires no computation as the maintenance policy is pre-specified as condition thresholds. The moderately complex model requires evaluation of agency and user costs for all possible policies using simulation to explore thousands of possible degradation trajectories. The complex model builds on the moderately complex model by computing the disruption cost as part of the objective function. The computation of the disruption cost is required for each possible policy and each of the thousands of degradation trajectories.

The models identify a maintenance policy that identifies actions based on the condition of the pavements and bridges. The models - are described and discussed in Chapter 3. The objective is to minimize total costs over the planning

horizon where total costs include the agency costs, the user costs and the disruption costs due to the selected activities. The complexity is characterized by the variations in the computational resource requirements, where the complex model requires 85 times the computational time used for solving the same problem as the simple model, while the moderate model uses about the same computational time as the complex model but has a slight variation in the computation which could make it perform better than the complex model under certain scenario. Figure 6.1 presents the metamodel framework.

The process begins by **defining the decision scenarios**. Then the **scenarios are labeled** with the preferred tool. The preferred tool is identified using an assignment rule that defines the criteria for comparing the outcomes of the models taking note of the efficiency concerning the complexities. For example, a simple model would be preferred if it produces the least life-cycle cost while only using a fraction of the resources required by the complex model, and a complex model may be suitable under certain scenarios regardless of the computational requirements. Next, the **labeled data is grouped** into classes based on scenario similarity. These **classes are analyzed** for the most preferred decision tool, as well as to uncover insights. Based on the insights, the number of models may be reduced if it is revealed that one or more of the models is not preferred in any of the scenario groups and the assignment rule would be updated to redistribute the models, excluding the dropped models. Updated labeled data is generated reflecting only the preferred models and this is used to **build a model of models** for predicting the preferred decision model for new scenarios. The building blocks of the framework are discussed extensively in the following sections.

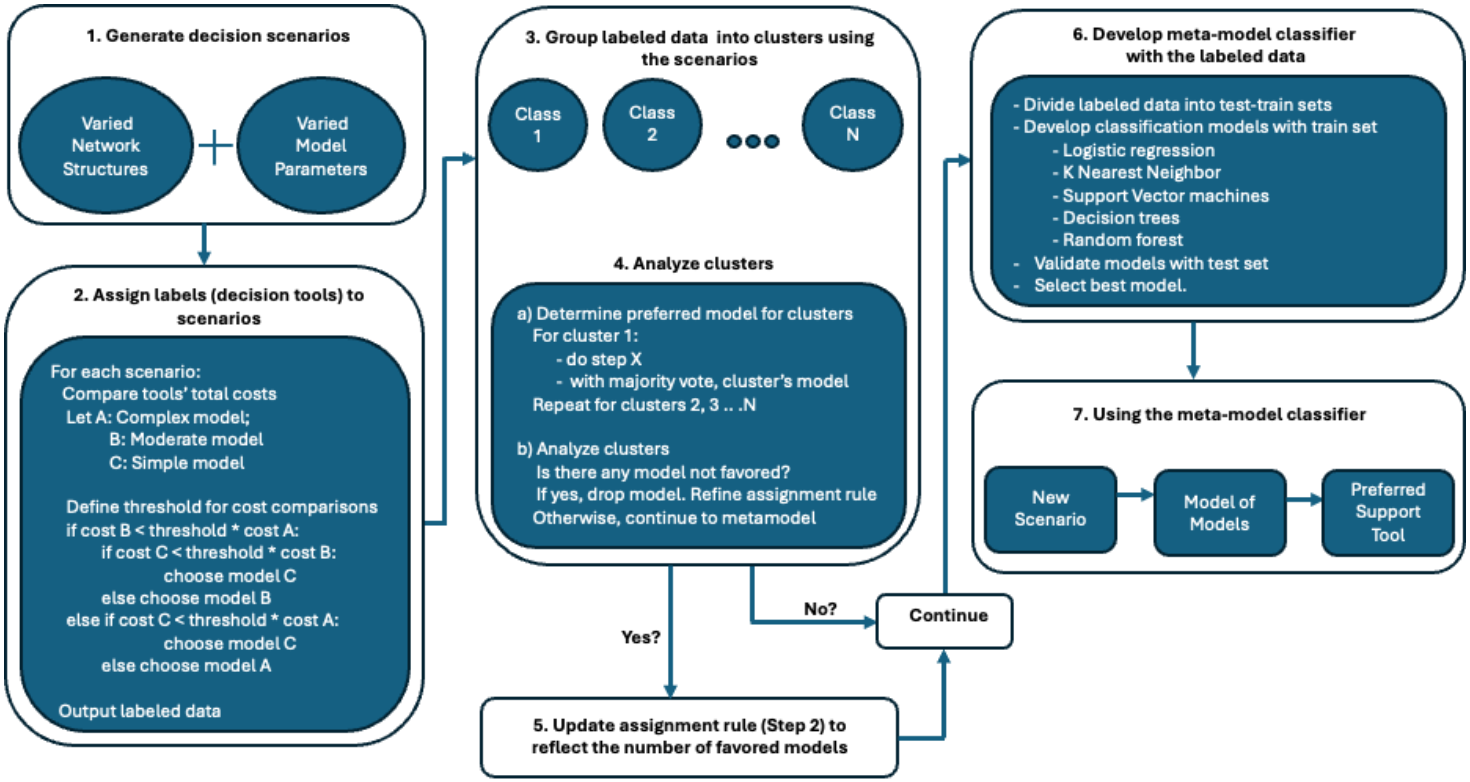


Figure 6.1: Procedure for the development of the meta-model for decision tool selection framework

6.2.1 Generating Decision Scenarios

In this study, a scenario is a combination of factors that will be considered to arrive at the decision outcomes or characterize the context and influence the decision outcomes. These factors are the same as those that directly influence the model including the network structure, origin-destination (OD) traffic demand, and traffic factor. Indirect factors are extracted from the network structures. These are attributes that characterize the network structure. A discussion of transportation network analysis and measures of network properties can be found in Section 5.3.2.

In this case study, network-level measures are selected, instead of local measures, to characterize the networks since they provide holistic information about the networks. Instead of using centrality measures, which typically assess the importance of nodes or edges in a network, the averages of these measures for all nodes or edges within the network are assessed as discussed in Section 5.3.2.1. Just like the average degree centrality that averages the individual node degrees, the average node betweenness, average edge betweenness, and average closeness centrality measures would each provide a single global value that characterizes the entire network's structure in terms of how well-connected or cohesive it is. Other global measures considered are size, density, diameter, average path length, clustering coefficient, degree assortativity, and global efficiency. Methods to compute these properties are also contained in Section 5.3.2.

Ten toy transportation networks of varying sizes and configurations (representing the structural arrangement of nodes and links, or connectivity) were created and can be found in Appendix A. Figures A-1 through A-10 show the

network connectivity with each node labeled with a numerical (1, 2….) and each edge or link labeled with a lowercase letter. Tables A-1 through A-10 show the properties for each edge (capacity, whether the edge is a bridge or pavement, length and number of lanes). For each network, up to three different configurations (designated X, Y, and Z) of the link capacities were systematically created to represent real-world scenarios where two networks of the same size and configuration can have different capacities. Some of these configurations were dropped from further consideration as the demand exceeded the network capacity. In practice, this is not realistic, and in the simulations, solutions could not be obtained as the traffic assignment program did not converge. Varying levels of OD traffic demand levels ranging from 1000 to 8000 were also established for each of the configured networks. Some of these values are also not realistic (as demand exceeds the network capacity) and in the simulation, the traffic assignment program did not converge. These scenarios were also dropped from further consideration and other values of demand explored as shown in Appendix A and summarized in Table 6.1. The end result is 100 different network configurations.

Also, a parameter in the model, i.e. the traffic factor that weights the traffic disruption costs in the network due to maintenance and rehabilitation activities, was set to four levels [0.25, 0.5, 0.75, 1.0]. Finally, the corresponding travel time indices (TTI), a global measure of network congestion, were computed for all the feasible configurations as discussed in Section 5.3.2.7.

Table 6.1: Number of demand scenarios for each network configuration and set of link capacities

Network Configuration	Capacity X	Capacity Y	Capacity Z	Total # of Demand Scenarios
1	6	4	-	10
2	4	4	4	12
3	4	4	4	12
4	4	4	3	11
5	8	-	-	8
6	4	4	4	12
7	4	4	4	12
8	3	-	-	3
9	4	4	-	8
10	4	4	4	12
Grand Total				100

A total of 400 decision scenarios were generated, each characterized by 15 variables: 1) number of nodes, 2) number of edges, 3) average degree centrality (ADC), 4) average betweenness centrality (ABC), 5) average closeness centrality (ACC), 6) average edge centrality (AEC), 7) diameter (Dia.), 8) network density (Density), 9) average shortest path length (APL), 10) average local clustering coefficient (ALCC), 11) assortativity (Assort.) 12) global efficiency (Eff.), 13) OD demand (OD), 14) travel time index (TTI), and 15) traffic factor. These manually generated scenarios mimic the unpredictability of the decision scenarios in real life.

6.2.2 Assigning Labels to Decision Scenarios

The three decision support tools are labeled A, B, and C.

- A represents the complex tool that enumerates all possible policies, computes the total cost of each policy over the planning horizon and selects the optimal policy that minimizes total costs.

- B represents the moderately complex tool that enumerates all possible policies, computes the total costs of each policy over the planning horizon but selects the policy that minimizes the sum of agency and user costs.
- C represents the simple tool that uses a pre-determined policy to compute the total costs.

For each decision scenario, each of the three decision support tools is applied to generate decision outcomes. The outcomes from these tools are a policy representing condition thresholds for each of the actions for pavements and bridges, and the total lifecycle costs, which is the sum of life-cycle agency, user, and disruption costs, for that policy. Note that the most complex tool (A) will always give the least total cost. A threshold value for the difference in total costs using different tools is defined and is tuned for best performance. This threshold value is the allowable percent difference in the total life-cycle costs between two models beyond which the more sophisticated (complex) tool is favored, implying that the cost difference is sufficiently large that the complex tool must be used. The threshold value is tuned to ensure substantial distribution of the size of scenarios assigned to each label. Initially, a threshold of 10% (i.e. cost ratio of 1.10) was selected as it is generally accepted amongst Departments of Transportation for costs to be estimated to within 5 to 15% variations (Hyari, Shatarat, & Khalafallah, 2017). However, in the case study used in this application, this threshold resulted in very little variation in the tools selected, suggesting that. This process was repeated for threshold values of 1.05 (or 5%), 1.01 (or 1%), and 1.005 (or 0.5), after which a value of 1.01 (i.e. 1% cost difference) was initially adopted for this case-

study. The value was later tuned to 1.05 when the number of tools reduced to two as discussed in Section 6.11 as recommended in Section 6.2.4.

The difference rule is first applied to tools A and B, and if the difference is less than the defined threshold, B is favored, and B is then compared with C. If the difference is less than the threshold, C is favored, otherwise B is favored. If, however, the difference between A and B is more than the threshold, A is favored and A is then compared with C. Again, if the difference between A and C is less than the threshold, C is favored, otherwise, A is favored. The result of this process is a set of labels, A, B, or C, for each decision scenario representing the appropriate model. This procedure was later repeated for two tools A and C based on the findings from Section 6.11.

6.2.3 Grouping Decision Scenarios

Using the unlabeled dataset of decision scenarios, cluster analysis is performed to group the scenarios based on similarities among them. K-Means clustering technique is adopted with hyperparameter tuning performed using the grid search method. Hierarchical clustering as well as the Elbow technique is used to determine the appropriate value of K, as appropriate.

6.2.4 Analyzing the Clusters

Next, the clusters are analyzed to uncover patterns in the decision scenarios that are likely to affect the outcomes. One hypothesis that motivates this study is that the complex tool will always be favored when the network is very congested whereas a simple tool is favored when the network is uncongested. Within the

moderate congestion level, perhaps the selection could be random. So, for each group, the relationship between the tools selected and the TTI values will be examined. Another hypothesis is that any one of the three models may not apply to any of the different groups of scenarios. If, after analyzing the clusters, it is revealed that one of the tools is not favored in any of the groups, this tool should be dropped and the assignment rule in Section 6.2.2 should be updated to reflect the number of tools remaining, otherwise, the step is avoided.

6.2.5 Selecting the Decision Tool for a New Decision Scenario

With the labeled data generated, a classification model is trained to determine the appropriate decision tools for new decision scenarios. Classification algorithms used are Logistic Regression, Support Vector Machine, K-Nearest Neighbor, Decision Tree, and Random Forest as discussed in Section 5.2. The algorithms are developed with consideration of the issues discussed in Section 5.2.9. The details of these are presented under Results and Discussion in Section 6.3.4. Principal Component Analysis is applied to reduce the noise in the dataset. The performance of all five classification algorithms is compared and the best selected to represent the meta-model classifier. This meta-model can then be used to guide decision-makers in tool selection.

6.3 Results and Discussion

This section presents the result of the data analysis using the 400 scenarios. The section discusses the computational requirements for the case study decision support tools, the exploratory data analysis of the dataset, the relationship between

congestion levels and decision models, the relationship between the network properties and the decision tools, and the evaluation of the classification tool for matching scenarios to decision support tools including the performance of the algorithms and the meta-model.

6.3.1 Computational Requirements of the Case Study Decision Support Tools

As discussed in Chapter 3 and (Atolagbe & McNeil, 2023c), the case study complex optimal models are relatively more computationally intensive compared with the simpler predefined threshold model. Using a MacBook Pro Apple M2 Chip with 16 GB RAM computer, the time required for the execution of an instance of the threshold-based tool and optimal thresholds-based tool optimized for agency cost on a network with 18 nodes and 28 edges are approximately 0.22 minute, and 18.5 minutes respectively. Figure 6.2 presents the run time analysis performed for the predefined threshold tool and the optimal threshold-based tool as a function of the number of edges in the network for the 10 toy networks shown in Appendix A. The analysis shows that on average the latter requires 85 times more computing resources. This computational burden is one of the motivations for developing the meta-model.

While computational effort continues to increase, models requiring the solution of network equilibrium problems and requiring many interactions to explore different deterioration trajectories are computationally burdensome.

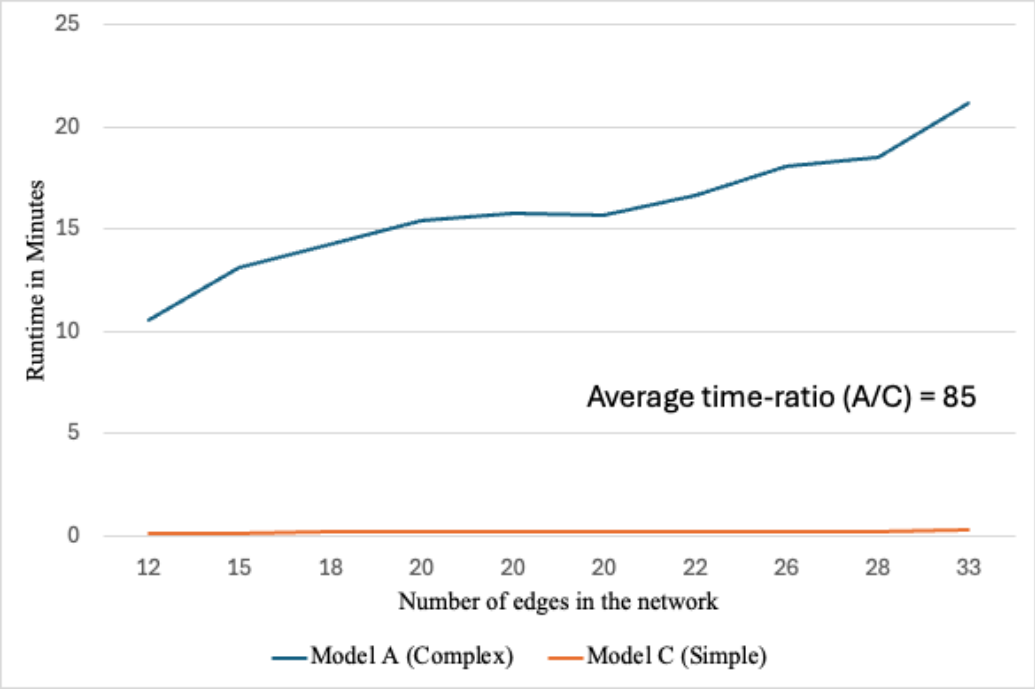


Figure 6.2: Runtime of models (in minutes) versus network size

6.3.2 Exploratory Data Analysis

The process for generating the experimental data is described in Section 5.3.1. The data has a dimension of 400 by 30 i.e. 400 scenarios (observations) and 30 variables. As the network properties are identical for each of the different traffic factors, the summary statistics are presented for the 100 unique combinations of network properties. The 30 variables are:

- Network properties (14): 1) number of nodes, 2) number of edges, 3) average degree centrality (ADC), 4) average betweenness centrality (ABC), 5) average closeness centrality (ACC), 6) average edge centrality (AEC), 7) diameter (Dia.), 8) network density (Density), 9) average shortest path length (APL), 10) average local clustering coefficient (ALCC), 11) assortativity (Assort.) 12) global

efficiency (Eff.), 13) OD demand (OD), and 14) travel time index (TTI)

- Cost variables for each tool (12): 1) total cost, 2) agency costs, 3) user cost, and 4) disruption cost
- Cost ratios (3): 1) B/A, 2) C/B, and 3) C/A.
- Traffic factor (1)

The analysis explores some of these variables (of interest) individually, as well as in combination with other variables. Table 6.2 provides summary statistics of the variables that represent the networks and constitute the inputs to the decision support models while Table 6.3 and Table 6.4 provide the summary statistics of the total cost over the planning horizon, the outputs from the decision support models, for traffic factors of 0.25 & 0.5, and 0.75 & 1, respectively.

In Table 6.2, summary statistics are presented for the 100 unique combinations of network properties. The average degree centrality ranges from 0.16 to 0.27, with a mean value of 0.20, indicating that there is a low connectivity per node across the networks. Other centrality measures, including average betweenness centrality, average closeness centrality, and average edge centrality all have low values also indicating limited connectivity per node. This small range and average values could be attributed to the simplicity of the toy networks. Other network measures such as density (mean of 0.20), diameter (mean of 6.33), and shortest path length (mean of 2.74) provide general insights on the structure of the networks, rather than the connectivity of the nodes. A mean network density of 0.20 indicates sparsity which may translate to very limited redundancies in the networks, and an average shortest path length of 2.74 suggests that there are moderately

efficient paths within the network since every node in the network is just a few nodes away from another. In addition, the degree assortativity (mean of -0.11) show that generally nodes in the networks have limited tendency to connect with others, while the global efficiency (mean of 0.49), indicates an average efficiency across the networks. The remaining variables, demand (OD volume) and TTI, are not typical network structural properties but are rather attributes of the traffic imposed on the network. The mean demand of 4855 implies the number of vehicles that can travel from the origin to the destination point in the network. Finally, using the following thresholds: 0 < TTI < 1.15 as uncongested; 1.15 <= TTI < 1.30 as moderately congested; and TTI >= 1.30 as congested (Subrat Mahapatra & Sadabadi, 2015), the TTI with a mean of 1.43 (> 1.3) shows that the networks are, on average, congested while its median of 1.05 (< 1.15) shows that more than 50% of the networks in the dataset are uncongested.

Table 6.2: Summary statistics of network properties

	ADC	ABC	ACC	AEC	Dia.	Density	APL	ALCC	Assort.	Eff.	OD	TTI
Count	100	100	100	100	100	100	100	100	100	100	100	100
Mean	0.20	0.14	0.38	0.14	6	0.20	2.74	0.09	-0.11	0.49	4855	1.43
Standard Deviation	0.03	0.02	0.03	0.03	1	0.03	0.27	0.09	0.19	0.03	2190	1.38
Minimum	0.16	0.09	0.32	0.08	5	0.16	2.29	0.00	-0.44	0.44	1000	1.00
25 %	0.18	0.13	0.36	0.13	5	0.18	2.50	0.00	-0.20	0.47	2750	1.01
Median	0.20	0.13	0.38	0.14	6	0.20	2.76	0.09	-0.14	0.49	4500	1.05
75%	0.23	0.16	0.41	0.16	7	0.23	2.90	0.11	0.06	0.51	6000	1.29
Maximum	0.27	0.18	0.44	0.19	8	0.27	3.22	0.32	0.21	0.55	8000	11.23

Key: ADC (Average Degree Centrality), ABC (Average Betweenness Centrality), ACC (Average Closeness Centrality), AEC (Average Edge Centrality), Dia. (Diameter), APL (Average Shortest Path Length), ALCC (Average Local Clustering Coefficient), Assort. (Degree Assortativity), Eff. (Global Efficiency), OD (Demand), TTI (Travel Time Index)

Table 6.3: Summary statistics of total cost ($ millions) with a traffic factor of 0.25 and 0.5

	Traffic Factor = 0.25						Traffic Factor = 0.5					
	A	B	C	B/A	C/B	C/A	A	B	C	B/A	C/B	C/A
Count	100	100	100	100	100	100	100	100	100	100	100	100
Mean	262.73	318.59	323.03	1.06	1.01	1.07	383.8	497.78	500.56	1.07	1.01	1.08
Standard Deviation	518.68	806.80	832.06	0.12	0.01	0.12	1041.2	1621.78	1614.93	0.15	0.01	0.15
Minimum	75.54	75.54	77.30	1.00	0.98	1.00	75.94	75.94	76.97	1.00	0.98	0.99
25 %	138.97	138.97	140.34	1.00	1.01	1.01	142.53	142.53	144.35	1.00	1.00	1.01
Median	165.27	165.27	167.13	1.00	1.01	1.01	176.47	178.05	179.89	1.00	1.01	1.01
75%	219.61	220.29	222.22	1.00	1.02	1.03	240.08	242.94	245.35	1.03	1.02	1.04
Maximum	5050.52	7770.76	8034.42	1.54	1.03	1.59	10006.08	15493.67	15397.08	1.56	1.06	1.58

Table 6.4: Summary statistics for total cost ($ millions) with a traffic factor of 0.75 and 1.0

	Traffic Factor = 0.75						Traffic Factor = 1.0					
	A	B	C	B/A	C/B	C/A	A	B	C	B/A	C/B	C/A
Count	100	100	100	100	100	100	100	100	100	100	100	100
Mean	501.45	675.89	686.86	1.09	1.01	1.10	617.27	856.80	871.34	1.10	1.01	1.11
Standard Deviation	1542.35	2410.33	2482.73	0.16	0.01	0.16	2029.37	3226.86	3321.34	0.17	0.01	0.17
Minimum	76.32	76.32	77.04	1.00	0.95	0.99	76.72	76.72	77.15	1.00	0.98	1.00
25 %	150.12	152.30	153.66	1.00	1.01	1.01	159.90	159.90	162.41	1.00	1.00	1.01
Median	187.49	187.49	189.93	1.00	1.01	1.02	194.61	203.53	207.05	1.00	1.01	1.02
75%	265.74	275.75	275.32	1.08	1.02	1.08	309.31	332.53	327.43	1.11	1.02	1.12
Maximum	14749.63	22905.77	23680.63	1.62	1.05	1.61	19315.80	30651.91	31590.23	1.62	1.04	1.64

In Tables 6.3 and 6.4, the total costs over the planning horizon are presented for four different values of traffic factors, 0.25, 0.5, 0.75 and 1.0. With a traffic factor of 0.25, the simple model is observed to have a significantly higher mean total cost (approximately $323 million) than the complex model (approximately $263 million) while the moderate model's mean total cost (approximately $319 million) is observed to be closer to that of the simple model. Similar observations are made across all the four values of the traffic factor. This may indicate that, on average the complex model is desirable due to the consistently least value. However, since the standard deviations are greater than the means for all the models, suggesting high variations in the costs, one could hypothesize that this observation varies for different scenarios. This could further be substantiated by the fact that the median values for the models are either very close (for B and C) or similar (for A and B) for all traffic factors. On the same note, the cost ratios provide relative cost comparisons: considering traffic factor of 0.25, the mean B-A cost ratio (B/A) of 1.06 and C-A cost ratio (C/A) of 1.07 suggest that moderate and simple models on average yield costs around 6-7% higher than the complex model, with the standard deviations indicating variations in this observation. Similarly, the mean C-B cost ratio (C/B) being 1.01 suggests that the simple model yields costs around 1% higher than the moderate model. Similar inference can be made for all four traffic factors, however, while the C-B cost ratio (C/B) is constant for all traffic factors, the cost ratios B/A and C/A are directly proportional to the traffic factor. These observations can inform the allowable cost ratio between the models that a decision-maker is willing to accept if the computational efficiency of the model is considered when selecting a model for decision-making.

The summary statistics are further illustrated by the set of Box and Whisker's plot shown in Figures 6.3 and 6.4 for the network variables and total cost respectively. In Figure 6.3 showing all the network variables, the box plot for TTI exhibits the presence of several outliers with more than 75% of the data below 2.0, but this is okay since those outliers essentially characterize congested networks and their presence is important for subsequent analysis. Average edge centrality and average local clustering coefficient also appear to have some outliers but are few compared to TTI. In Figure 6.4, the box plots for total costs are presented for a traffic factor of 0.25. The three total cost variables appear to have a comparable number of outliers. This may likely be attributed to the extreme values in congestion values (TTIs) which drive the disruption costs – a component of the total costs. On the other hand, of the three cost ratio variables, C-B cost ratio (C/B) appear to have fewer outliers compared with B-A cost ratio (B/A) and C-A (C/A) ratio which have several outliers, suggesting that the cost differences are inconsistent across different scenarios, highlighting the value in being able to match models to different scenarios.

Box plots for other traffic factors (0.5, 0.75, and 1) are shown in Appendix B (Figures B-1 to B-3). Consistent with the role the traffic factor plays in the models, the total cost increases as the traffic factor increases. However, the relative values remain consistent.

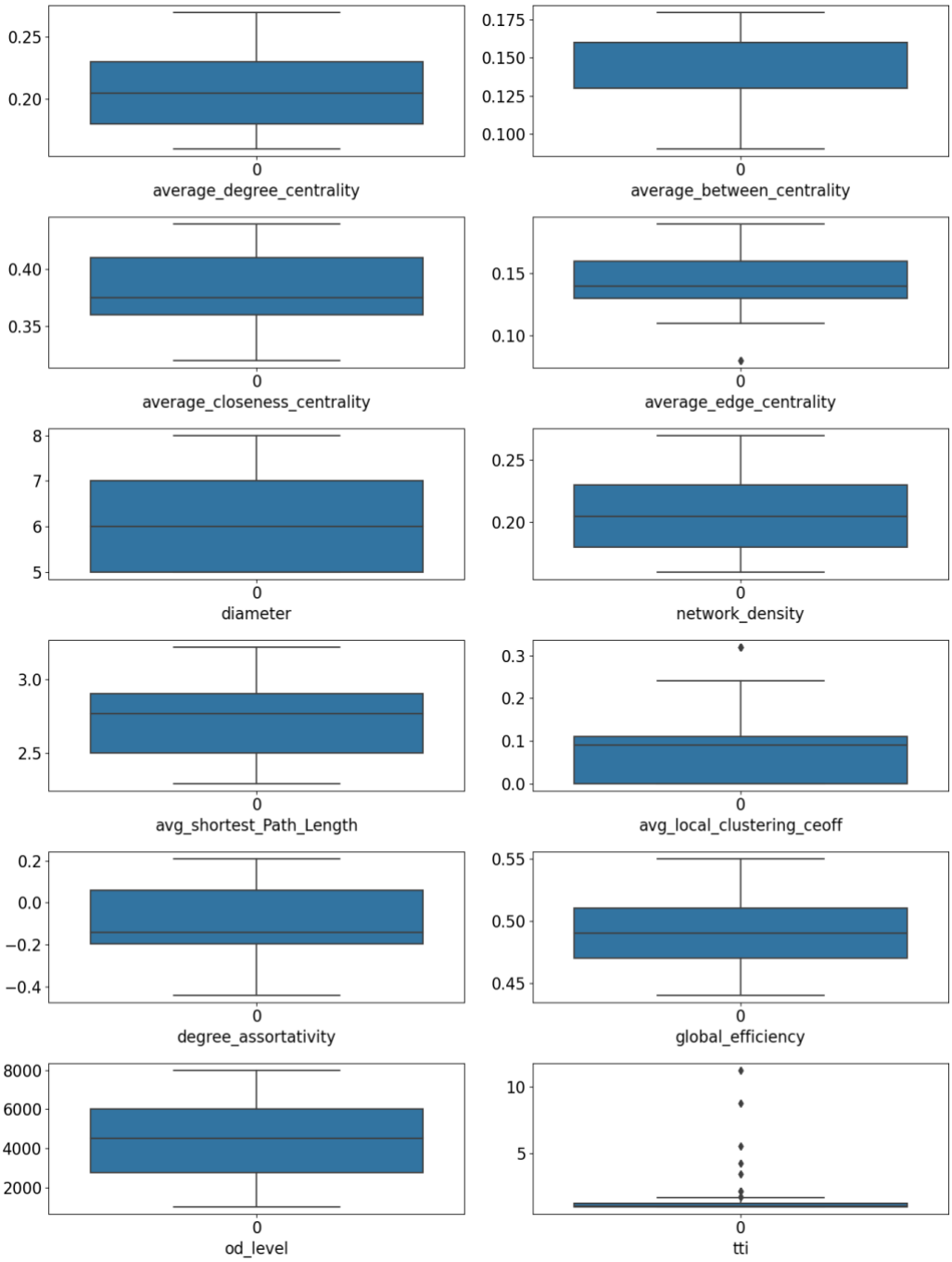


Figure 6.3: Box and Whisker's plot of the network variables

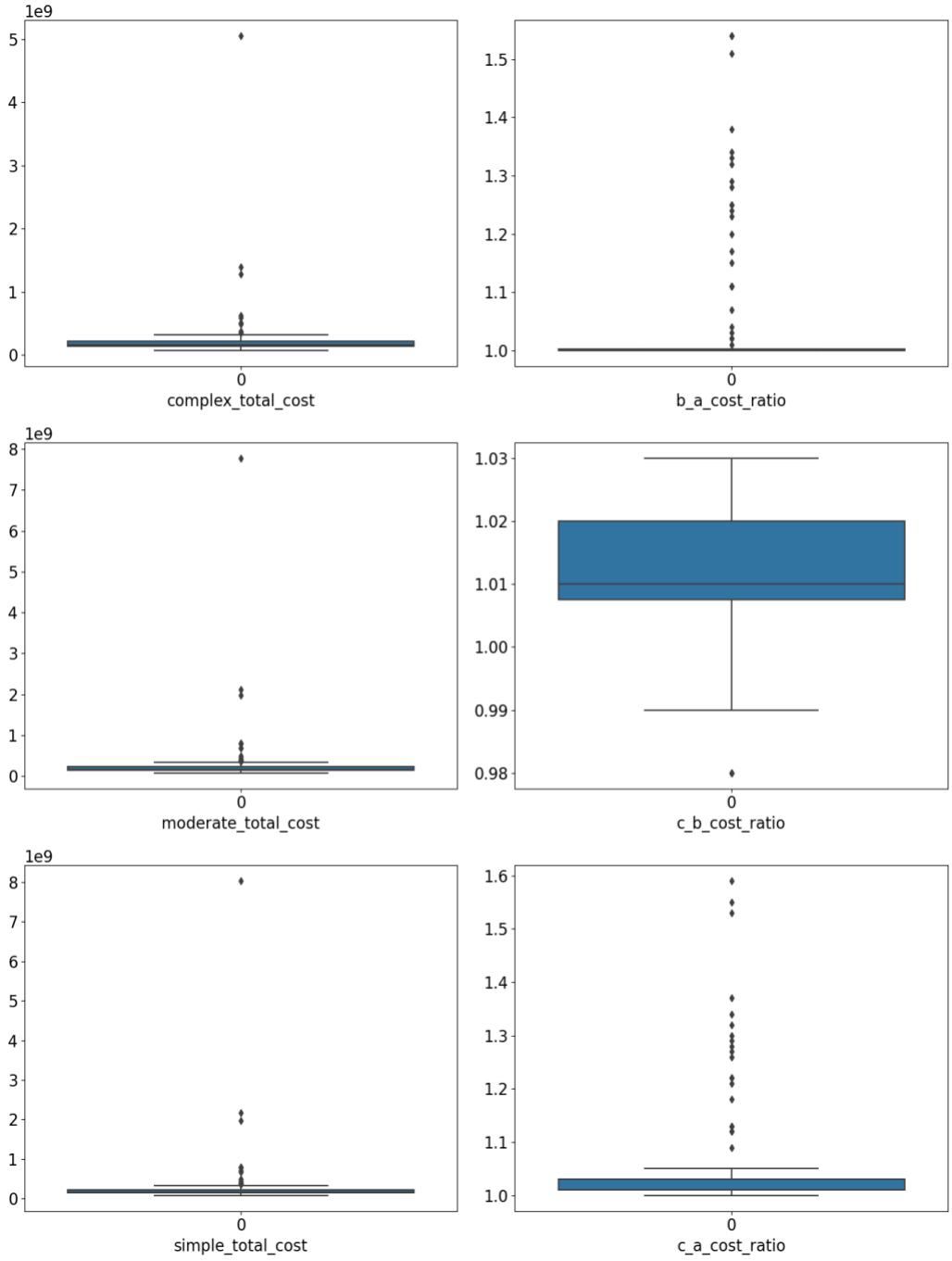


Figure 6.4: Box and Whisker's plot of total cost (Traffic Factor= 0.25)

Histograms of these variables are presented in Figures 6.5 and 6.6 to visualize the univariate distributions. In Figure 6.5, the majority of the histograms are right-skewed, especially for average betweenness centrality, clustering coefficient, OD level, and TTI. This implies that most networks in the dataset have relatively low values for these properties, but there are a few networks with much higher values, which may indicate outliers. This is the case with the TTI. Some of the histograms, such as average shortest path length and degree assortativity, appear to be normally distributed which makes them potentially good predictors, while average closeness centrality and density appear to be uniformly distributed suggesting balanced proportions of different networks with these properties.

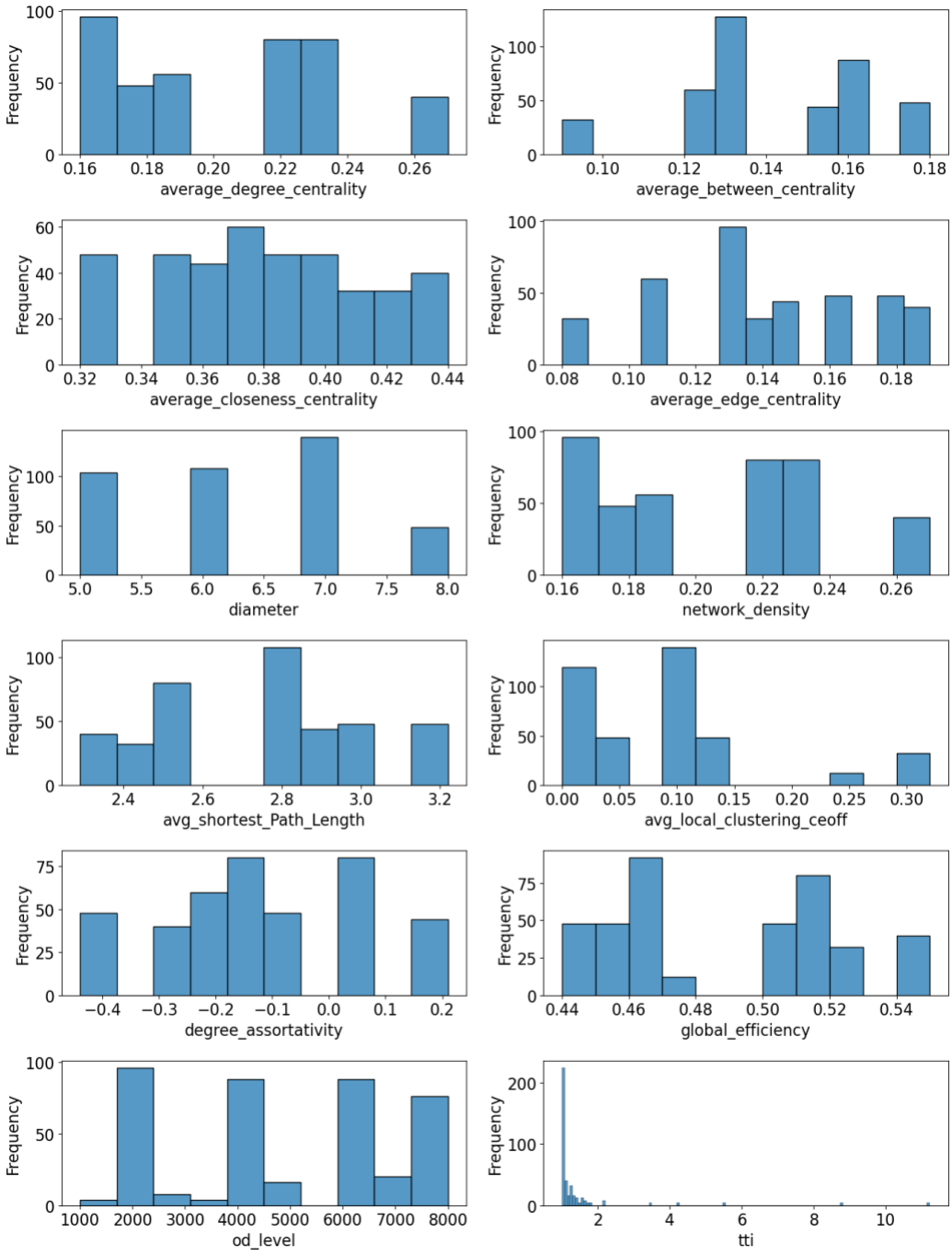


Figure 6.5: Histograms of the network properties

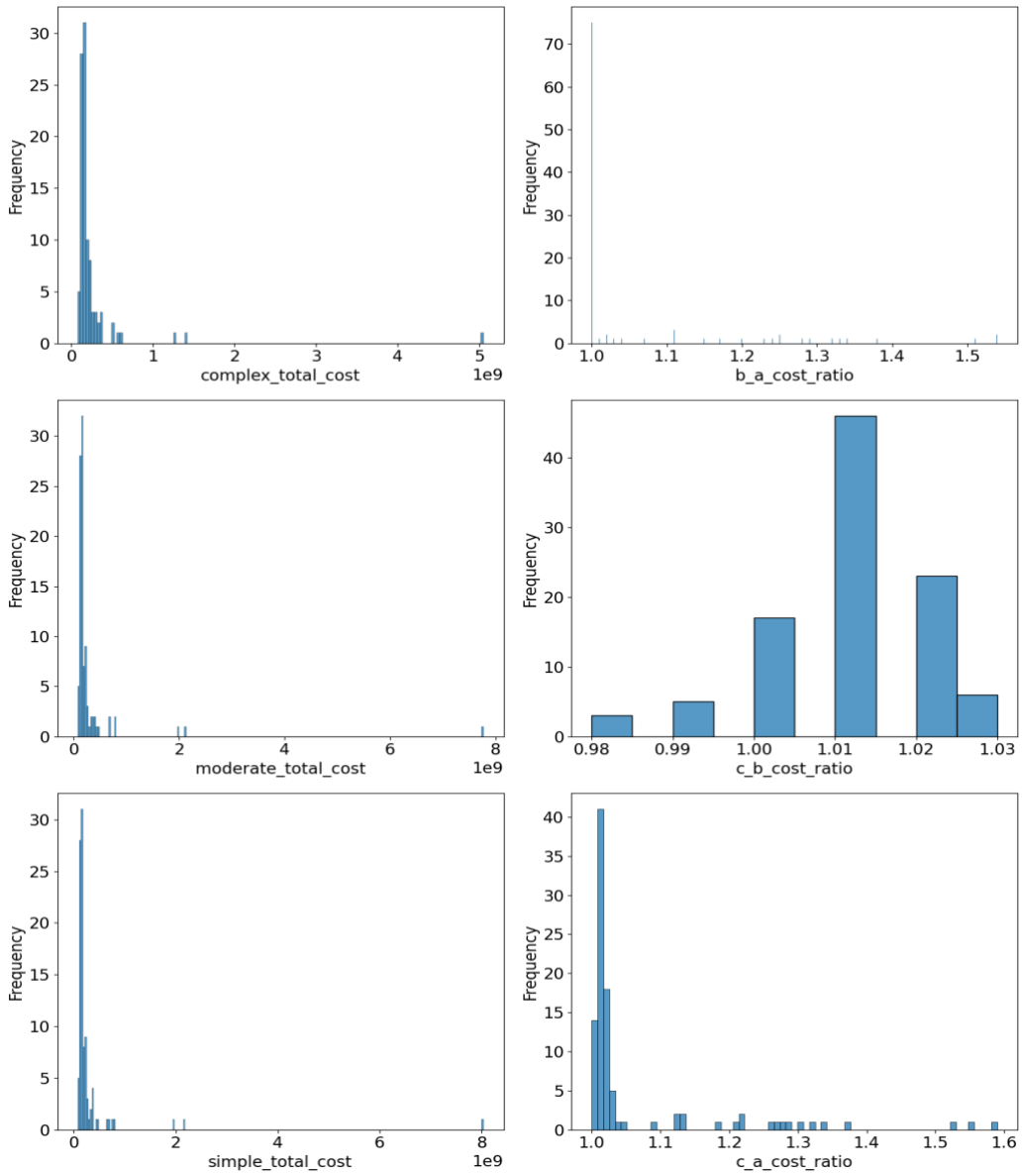


Figure 6.6: Histograms of cost properties (Traffic Factor = 0.25)

In Figure 6.6, the histograms of cost variables are presented for traffic factor of 0.25. Histograms for traffic factors of 0.50, 0.75 and 1.0 are included in

Appendix B. All but one histogram for the C-B cost ratio is right skewed, indicating the possibility of extreme values which may be due to large infrastructure costs under certain scenarios. The histograms of the cost ratios (B-A cost ratio, C-B cost ratio, and C-A cost ratio) generally suggest that the cost differences between the pairs of tools are mostly close to one suggesting that the meta-model assignment rule threshold, i.e. percent difference in the costs, could be set close to zero.

A correlation plot showing the linear correlation coefficients among all the variables of interest is shown in Figure 6.7. Average degree centrality, global efficiency, and average closeness centrality measures are highly correlated while average edge centrality and network density are also highly correlated. Global efficiency and degree assortative are moderately correlated. Similar details can be extracted for pairs of variables from the plot. The cost variables have weak correlations with the network structure properties suggesting that they do not have a linear relationship, the absence of which could mean the existence of a latent or non-linear relationship between them. Owing to this, nonlinear models including SVM, KNN, and random forest are selected for the meta-model development. Likewise, PCA is performed on these variables to eliminate noise and capture the most possible variance in the data with fewer variables.

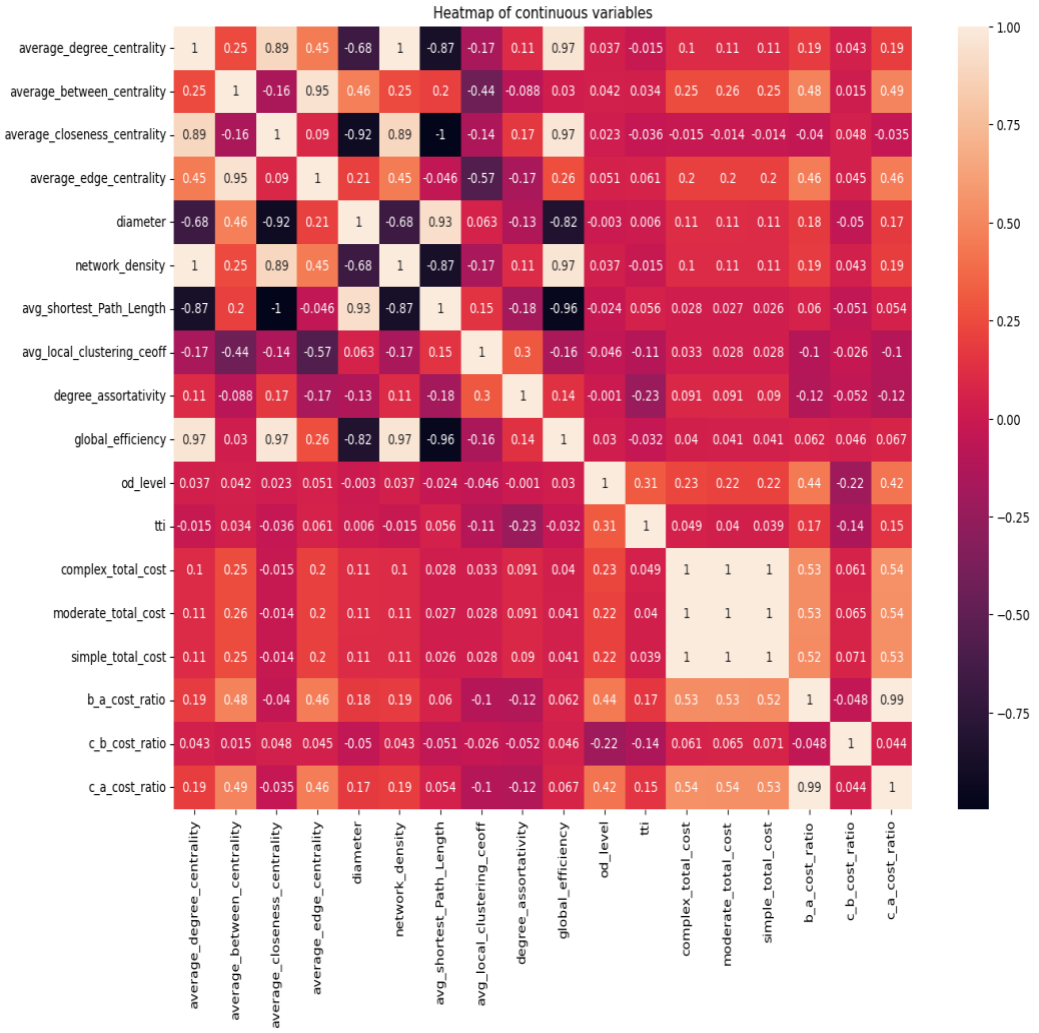


Figure 6.7: Correlation plot of variables of interest

6.3.3 Relationship between Congestion Levels and Decision Models

Previously, it was hypothesized that there could be a relationship between the congestion levels of the networks and the decision models (Atolagbe & McNeil, 2023c). It was hypothesized that, perhaps a decision maker is better off using a

complex model only when the network is congested, a moderate model when the congestion level is moderate, and a simple model when the network is uncongested.

A Chi-Square test (Montgomery, Runger, & Hubele, 2009) was implemented for this purpose. The Chi-Square test involves first defining a Null Hypothesis (h_o) and Alternative Hypothesis (h_1). The null hypothesis states that there exists no significant difference between the observed and expected frequencies while the alternative hypothesis states otherwise. Next, observed frequency of occurrence of each category is determined, usually by developing a contingency table – a table that shows the number of occurrences of all possible combinations of categories in the variables of interest. Next, assuming that the null hypothesis is true, the expected frequency of occurrence of each category is calculated as follows: $E = \frac{\text{Row Total x Column Total}}{\text{Grand Total}}$. Next the Chi-Square statistic χ^2 is calculated as: $\chi^2 = \sum \frac{(O-E)^2}{E}$ where O is the observed frequency, and the summation is all over the cells in the contingency table. Next, a degree of freedom is calculated for the contingency table as: $df = (r-1)\ x\ (c-1)$ where r is the number of rows in the table and c is the number of columns in the table. Using the Chi-Square distribution table, the probability of observing a Chi-Square statistic that is greater than or equal to the calculated value, at the calculated degree of freedom is computed. This is the p-value, and it is compared with a desired alpha significance level. If the p-value is less than the significance level, the null hypothesis is rejected, indicating that there is significant statistical relationship between the variables. If otherwise, the null hypothesis is not rejected, implying no significant statistical relationship between the variables.

Here, The TTIs are first converted to congestion levels using the following threshold: 0 < TTI < 1.15 as uncongested; 1.15 <= TTI < 1.30 as moderately congested; and TTI >= 1.30 as congested. A is defined as complex model, B as moderate model, and C as simple model. Table 6.5 is a contingency table showing the distribution of these two variables.

Table 6.5: Contingency table for congestion level and decision model

	Decision Model		
Congestion Level	A	B	C
Uncongested	50	8	34
Moderately Congested	45	58	153
Congested	24	5	23

The Chi-Square test was performed using the "stats.chi2_contingency" submodule of the Python statistical package "scipy". The resulting Chi square statistic for this test and the corresponding p-value are 53.3 and 7.35e-11 respectively. Since the p-value is far less than alpha significance level of 0.05, we conclude that there is a significant association between congestion level and model choice. However, the Chi-Square test does not explain a causal relationship. Inspection of Table 6.5 suggests that Model C is the most appropriate for moderately congested networks but further analysis is warranted.

6.3.4 Relationship between the Scenarios and the Decision Models

In the previous section, it was established that there exists a relationship between the level of congestion and the decision model choice. Since there are other variables characterizing the networks, here, the possibility of these variables

influencing the decision model choice is explored. Clustering analysis was adopted to demonstrate this. K-Means clustering analysis was implemented to characterize the network properties (i.e. scenarios) with the corresponding cost variables in the dataset. The variables selected for clustering are the number of nodes, number of edges, average degree centrality, average between centrality, average closeness centrality, average edge centrality, diameter, network density, average shortest path length, average local clustering coefficient, degree assortativity, global efficiency, OD volume, and TTI.

To select the number of clusters for K-Means clustering, two methods were adopted, inspecting the dendrogram from hierarchical clustering performed on the data, and the Elbow method. Hierarchical clustering was performed using the "cluster.hierarchy" module of " scipy" Python package. Figure 6.8 is a dendrogram generated from hierarchical clustering.

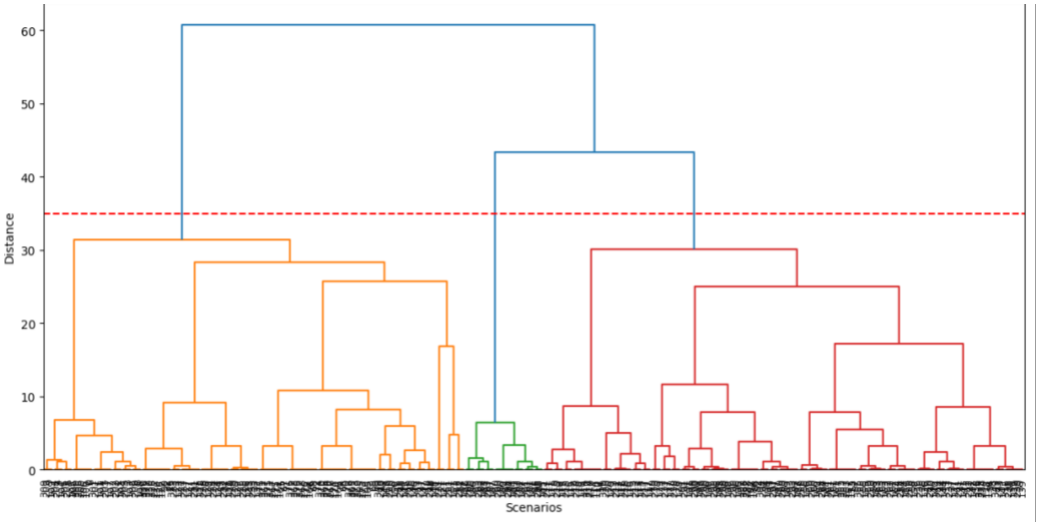


Figure 6.8: Dendrogram from hierarchical clustering on the dataset

It is observed in Figure 6.8 that the network decision scenarios can be clustered into three classes. Using a value of K=3, a K-Means cluster analysis was performed. Figure 6.9 is a breakdown of the models in each of the three clusters. Model C is the most frequently favored in the Clusters 1 and 3 while Model A is the most frequently favored in Cluster 2. Although there is an indication that Model B might have been favored in certain instances, it is not enough to characterize the entire scenarios in any of the Clusters with Model B. Taking another look at Figure 6.8, although there appears to be three clusters, the size of one cluster is so small relative to the others, perhaps, it is sufficient to only have two clusters from this dataset.

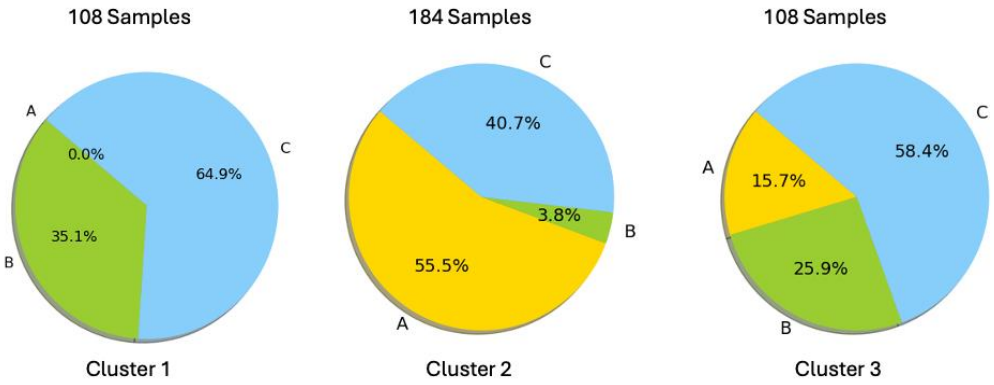


Figure 6.9: Model selection in the three clusters from hierarchical analysis

Figure 6.9 is an elbow curve that is developed to select the optimal K value for K-means clustering. It is plotted as the within-cluster-sum-of-squares values obtained for different values of K used in K-means clustering algorithm. It is

observed that K=2 is the suitable number of clusters. Using K=2, Figure 6.10 is the breakdown of the decision model choices in each of the clusters.

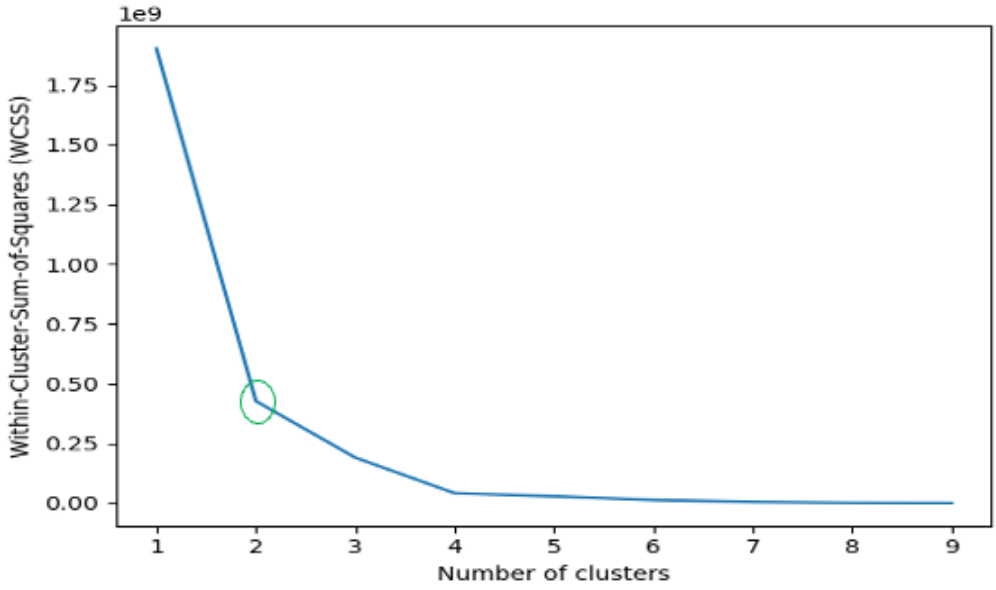


Figure 6.10: The elbow method for selecting K

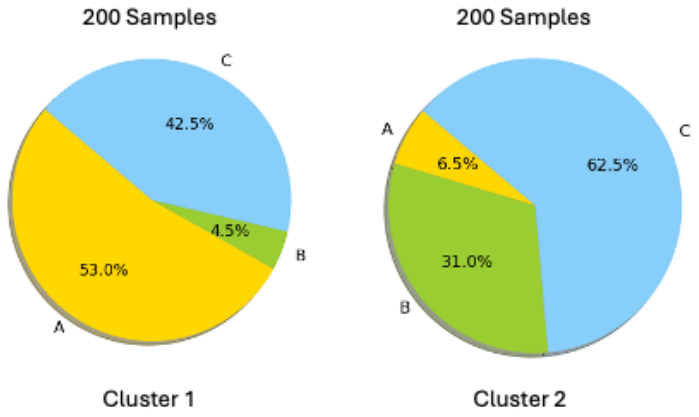


Figure 6.11: Model selection in the two clusters from the elbow method

In Figure 6.11, Model A is the most frequently favored in the Cluster 1 while Model C is the most frequently favored in Cluster 2. Again, although there is indication that Model B might have been favored in certain instances, it is not enough to characterize the entire scenarios in any of the Clusters with Model B.

Table 6.6 presents the summary statistics for the variables in the two clusters from the K-means analysis. It appears that Cluster 1 is characterized by high average TTI value (i.e. high congestion level, 1.88 although there are outliers) while Cluster 2 is characterized by low average and median TTI value (i.e. low congestion level, 1.06, 1.01 respectively, although there seems to be an outlier). Also, since the minimum and median TTI values in Cluster 1 are 1.02 and 1.21 respectively, it can be said that more than 50% of the data in Cluster 1 may fall in the region of moderately congested or uncongested traffic levels. Likewise, the maximum value of 1.64 in Cluster 2 suggests that a few scenarios may fall in the region of moderately congested or congested traffic levels. Thus, it is evident that while Cluster 1 encompasses congested networks and Cluster 2 encompasses uncongested networks, moderately congested networks may fall in either Cluster. This underscores the need to build a classification model that ascribes models to these scenarios more efficiently.

The findings from this analysis indicate that Models A and C can be used to characterize the scenarios in the dataset, suggesting the asset manager can pay more attention to these two models in his toolbox as well as the need to build a classification model to effectively ascribe decision models to the scenarios. As discussed in Section 6.2.2, it is necessary to update the labels of the dataset to reflect two classes of tools rather than three.

Table 6.6: Summary statistics of TTI values in the clusters from the K-means clustering analysis

	Count	Mean	Standard Deviation	Minimum	25%	Median	75%	Maximum
Cluster 1	200	1.80	1.88	1.02	1.06	1.21	1.54	11.23
Cluster 2	200	1.06	0.13	1.00	1.00	1.01	1.04	1.64

6.3.5 Evaluation of the Meta-model Classifier Performance

The last phase of the metamodel framework development is to build a classification model that can predict the appropriate tool to use between a complex and simple decision support model under different decision scenarios. The predictor variables for this model, just as for the clustering analysis, are the variables that characterize the network including number of nodes, number of edges, average degree centrality, average between centrality, average closeness centrality, average edge centrality, diameter, network density, average shortest path length, average local clustering coefficient, degree assortativity, global efficiency, OD volume, and TTI. Principal components analysis was performed on the feature sets to reduce the number of variables to six principal components which captures around 95% of the variance in the data as shown in Figure 6.12.

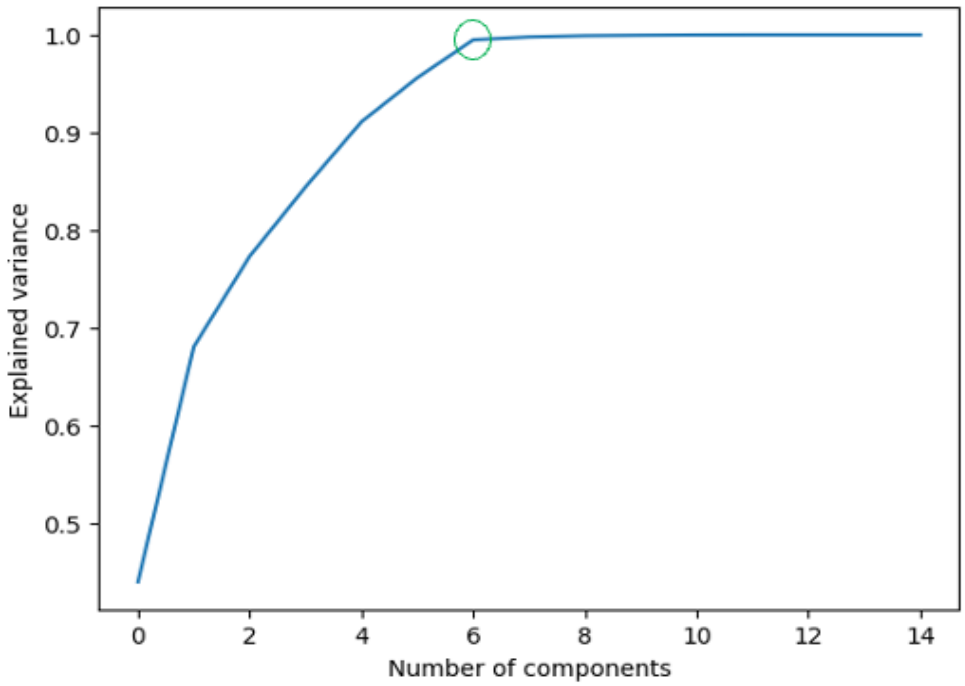


Figure 6.12: Cumulative explained variance explained versus number of principal components

Table 6.7: Factor loadings from the principal components analysis

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10	PC11	PC12	PC13	PC14	PC15
nodes	-0.35	0.22	0.05	-0.05	0.00	-0.03	-0.03	-0.11	-0.53	0.04	0.11	0.02	-0.72	-0.03	-0.01
edges	-0.27	0.37	0.03	0.02	0.00	0.07	-0.08	-0.05	-0.45	-0.02	-0.50	-0.15	0.49	0.23	0.04
ADC	0.38	0.06	-0.04	0.08	0.00	0.19	-0.14	0.13	-0.05	-0.24	-0.37	-0.02	-0.23	-0.27	0.67
ABC	0.12	-0.47	-0.16	0.18	0.00	0.13	-0.05	-0.13	-0.19	0.73	-0.29	0.08	-0.07	0.06	0.01
ACC	0.34	0.24	0.04	-0.05	0.00	-0.04	0.03	0.04	-0.39	0.11	0.26	0.67	0.27	-0.26	-0.04
AEC	0.21	-0.43	-0.08	0.06	0.00	0.07	-0.06	-0.50	-0.41	-0.44	0.26	-0.19	0.14	0.10	0.02
Dia.	-0.26	-0.35	-0.13	0.16	0.00	0.13	-0.11	0.75	-0.30	-0.12	0.20	-0.06	0.12	-0.10	-0.01
Dens.	0.38	0.06	-0.04	0.08	0.00	0.19	-0.14	0.13	-0.05	-0.24	-0.37	-0.02	-0.22	-0.06	-0.73
APL	-0.34	-0.26	-0.04	0.06	0.00	0.09	-0.04	-0.09	0.17	-0.34	-0.26	0.69	-0.08	0.31	0.05
ALCC	-0.15	0.29	-0.19	0.39	0.00	0.60	-0.40	-0.20	0.20	0.09	0.30	0.01	0.05	-0.08	-0.01
Assort	0.03	0.17	-0.41	0.63	0.00	-0.18	0.60	-0.01	-0.02	-0.09	-0.02	-0.01	-0.04	0.02	0.00
Eff.	0.37	0.16	0.00	0.01	0.00	0.06	-0.07	0.25	-0.05	0.07	0.22	0.00	-0.13	0.82	0.12
OD	0.02	-0.03	0.53	0.59	0.00	-0.47	-0.39	-0.01	0.02	0.00	0.00	0.01	0.00	0.00	0.00
TTI	0.00	-0.07	0.68	0.13	0.00	0.51	0.50	0.02	-0.03	0.01	0.01	-0.02	0.00	0.00	0.00
TF	0.00	0.00	0.00	0.00	-1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Key: ADC (Average Degree Centrality), ABC (Average Betweenness Centrality), ACC (Average Closeness Centrality), AEC (Average Edge Centrality), Dia. (Diameter), APL (Average Shortest Path Length), ALCC (Average Local Clustering Coefficient), Assort. (Degree Assortativity), Eff. (Global Efficiency), OD (Origin-Destination Volume), TTI (Travel Time Index), TF (Traffic Factor).

Table 6.8: Percent explained variance captured by the principal components

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10	PC11	PC12	PC13	PC14	PC15
Variance	44.08	24.08	9.26	7.10	6.67	4.51	3.88	0.30	0.12	0.05	0.03	0.01	0.00	0.00	0.00

Table 6.9: Definition of hyperparameters for classification algorithms

Model	Selected Hyperparameters
LR	max_iter = 1000; C = [0.01, 0.1, 1, 10, 100]; penalty = [L1, L2]; solver = [liblinear]
SVM	C = [0.1, 1, 10]; kernel = [linear, rbf]
KNN	n_neighbors = [3, 5, 7, 9]; weights = [uniform, distance]
DT	max_depth = [5, 10, 15]; min_samples_split = [2, 5, 10]
RF	n_estimators = [50, 100, 200]; max_depth = [5, 10, 15]

Table 6.10: Summary of classification models with the principal components

Model	Best Parameters	Accuracy	Precision	Recall	F1 Score
LR	C =10; penalty = L1; solver = liblinear	87.50	87.37	87.50	87.43
SVM	C = 1; kernel = rbf	94.17	94.12	94.17	94.13
KNN	n_neighbors = 7; weights = uniform	94.17	94.12	94.17	94.13
DT	max_depth = 10, min_samples_split = 2	94.17	94.12	94.17	94.13
RF	max_depth = 10; n_estimators =100	95.83	95.89	95.83	95.85

Table 6.7 presents the factor loadings from the principal components analysis while Table 6.8 presents the percentage variance explained the principal components.

PC1 captures the most variance (44%) in the data and it is mostly correlated with, and as such influenced by, the number of nodes, average degree centrality, average closeness centrality, network density, and global efficiency. PC2 captures 24% of variance in the data and it is influenced by number of edges, average betweenness centrality, average edge centrality, and diameter. This implies that 68% of the variations in the data is captured by network size and centrality measures, as well as some connectivity measures. Additional variance due to connectivity measures is captured PC 4 and PC6 with combined explained variance of about 12% where PC4 is mostly driven by assortativity and PC6 by average local clustering coefficient. PC3 is mostly influenced by TTI indicating that 9% of the variations in data is likely driven by the congestion levels across all the networks. PC5, explaining about 6% of the variance in the data, is completely influenced by traffic factor. Overall, the features in the data are substantially represented by the first six PCs, capturing about 95% of the variance in the process. These six PCs are used as independent variables for training the classification models.

The target variable is the decision tool choice, 0 for simple tool and 1 for complex tool. Five classification algorithms were selected to develop a binary classification mode. These are Logistic Regression, K-Nearest Neighbors (KNN), Support Vectors Machine (SVM), Decision Tree, and Random Forest. The dataset

is first divided into the training set and the test set at a ratio of 70:30 and random state, a parameter that is established to ensure consistency in the outcome of the result every time the model is run, is set to 42. Grid search technique was adopted to tune the hyperparameters by exploring all feasible instances of each of the five classification models using the provided values of the hyperparameters in Table 6.9. The best-performing instance of each of the models was selected.

Table 6.10 summarizes the performance of the models. Evaluation metrics assessed are accuracy, precision, recall, and F1-score. Logistic regression yielded the poorest performance. KNN, SVM and Decision Tree models have similar performance. Random Forest performed with accuracy and F1 score of approximately 96%. This model was achieved with a maximum depth of tree of 10 and 100 estimators. The accuracy score indicates that on average, the meta-model classifier will be 96% correct in its prediction of the decision tool to use for new decision scenarios. Likewise, the F1-score indicate that meta-model classifier is well-balanced in determine the correct predictions with only 4% chance of making errors.

An application of the metamodel framework to a small case-study network in Newark, Delaware based on realistic data is discussed in Appendix C. There, it is shown than the framework can indeed be applied to networks other than those used to train and validate the framework. The analysis showed that the simple tool can simply be applied without necessarily running of the tools.

6.4 Concluding Remarks

A meta-model framework for matching decision supports to decision scenarios is presented. Three related decision support tools for highway network life-cycle maintenance cost assessment were applied to different decision scenarios that are characterized by the decision variables. The difference in output cost values from the three models was compared using a threshold value that is defined in a model assignment rule. With the rule, preferred decision support models were assigned as labels to the scenarios. The properties of the scenarios were analyzed and a machine learning-based meta-model classifier was developed using the labeled data. The outcomes of the study showed that indeed the decision scenarios exhibit an associative relationship with the decision models. The procedure also shows that it is possible to reduce the catalog of decision support tools available to solve the same problem by identify the ones that will not apply to a group of scenarios with similar characteristics. The performance of the meta-model classifier shows that the proposed framework can predict the most preferred decision support tools to use for previously unseen scenarios as illustrated with the case-study network in Newark, Delaware.

Overall, this analysis presents an opportunity for decision makers to benchmark emerging support tools with existing, legacy tools. It also presents an opportunity for researchers to demonstrate the benefits in new sophisticated tools against existing simpler tools. Finally, decision maker can make quick decisions with the most likely optimal model when making several iterations of decisions

which is usually the case in the management of infrastructure systems where many alternative scenarios would normally be explored.

Chapter 7

CONCLUSIONS, RECOMMENDATIONS AND FUTURE WORK

7.1 Summary, Conclusions and Recommendations

This research presents the need for a framework to make transportation asset management (TAM) decision-support tools more useful to decision-makers. Although there are several existing decision support tools that address the challenges encountered in TAM, there continues to be a proliferation of decision tools or frameworks. No doubt, this is often because of the desire to make an existing tool or framework more robust or the need to exploit newly understood analytical concepts or emerging technology. Unfortunately, in the process of providing a better framework, new challenges arise in the form of complexity of the framework, uncertainty in the decision variables of the framework, obscurity in the results of the model, and to an extent, skepticism of decision makers at highway agencies in the application of the tools.

Furthermore, developing new models does not always render existing tools, sometimes legacy ones, inconsequential. It may be observed that decision-makers in highway agencies are much more comfortable using existing tools because of the "switching cost" of the new support tools as well as the complexity and skepticism of the new frameworks. Perhaps, the existing tools might still be relevant for certain

decision scenarios and if such instances can be known, then the older, existing model can be used, and the decision-makers can make quicker decisions with less skepticism.

This dissertation focuses on how to ensure that emerging technologies upon which newer decision support tools are built are better leveraged thus enabling more timely and efficient decisions for TAM systems. Specifically, the objectives of this dissertation are to demonstrate the benefits of using a variance-based sensitivity analysis technique, over local methods, for identifying less consequential input variables and parameters for decision tools thus increasing model fidelity, as well as to propose and demonstrate a meta-model procedure for selecting appropriate support tools for decisions according to the scenarios encountered using applicable machine learning techniques.

The research uses a case-study built around three decision support tools and a toy network. The data and model structure are derived from W. Zhou et al. (2022). Three decision support tools are developed. The first, and most complex, solves a multi-class asset maintenance prioritization and scheduling problem considering traffic impacts to minimize the total cost of improvement investment, user costs, and traffic delays due to downtime resulting from the implementation of the actions over a specified planning horizon. This tool requires the solution of a network equilibrium model to compute the disruption cost. The model is solved by enumerating all possible maintenance policies for pavements and bridges. The

second model solves the same problem but enumerates all policies to minimize agency plus user costs. The third model simply applies a specified policy.

Focusing on the optimization model for total costs, a global sensitivity analysis technique, called Sobol's method is used to identify the importance of the model's input variables and parameters. The analysis showed that, unlike local methods, where the sensitivity of the model's outcomes to the inputs are examined one at a time, the Sobol method showed a superior ability to identify the interactions among parameters and their importance. That is, the analysis showed that one must be careful in dealing with the parameters in complex decision support tools as there is a tendency to erroneously underestimate the influence of some parameters on the output when they are considered independently as opposed to their combined effects which may reveal that they are otherwise consequential to the outcome of the model. Examining the variables as demonstrated in this dissertation could be very beneficial as the influence of the selected values of parameters can now be controlled by fixing some factors that have low sensitivity indices in the model thus simplifying the model and potentially reducing their computational requirements since the components of the tools that depends upon such variables may simply be avoided.

A tool-matching framework, a meta-model framework, for matching decision support tools to decision scenarios in TAM has also been developed and its application demonstrated. The three related decision support tools for highway network life-cycle maintenance cost assessment were applied to different decision

scenarios that are characterized variables related to the context. The difference in output cost values from the three models was compared using a threshold value that is defined in a model assignment rule. With the rule, preferred decision support models were assigned as labels to the scenarios. The properties of the scenarios were analyzed, and a machine learning-based meta-model classifier was developed using the labeled data. The outcomes of the study showed that indeed the decision scenarios exhibit an associative relationship with the decision models. The procedure also shows that it is possible to reduce the catalog of decision support tools available to solve the same problem by identifying the ones that will not apply to a group of scenarios with similar characteristics. The performance of the meta-model classifier shows that the proposed framework can predict the most preferred decision support tools to use for previously unseen scenarios.

This presents an opportunity for decision-makers to benchmark emerging decision support tools with existing, legacy tools. It also presents an opportunity for researchers to demonstrate the benefits of new sophisticated tools against existing simpler tools. Likewise, decision makers can make quick decisions with the most likely optimal model when making several iterations of decisions, which is usually the case in the management of infrastructure systems where many alternative scenarios would normally be explored.

7.2 Limitations

One challenge encountered in the implementation of the concepts demonstrated in this research is the computational requirement. For both objectives

explored, simulations involving several runs of the decision tools for different iterations were necessary. Increasing the simulation size will yield improved results, particularly for Sobol's analysis, but this exercise can become prohibitive if an instance of the runs requires an excessively large run time. It is recommended that researchers attempting to perform similar experiments have access to high-performance computing resources.

Also, development of the accurate decision scenarios is a function of the understanding of the prevailing decision-making process for the tools explored. Therefore, it is recommended that developers of the meta-model must have knowledge of the related decision support tools, as well as the development of meaningful decision scenarios upon which the meta-model would be built.

7.3 Contributions

This research contributes to the field of transportation asset management in the following areas:

- Recognition of the challenges presented by the implementation of complex decision support tools.
- Demonstration of the need for rigorous local and global sensitivity analysis of decision support tools.
- Application and interpretation of global sensitivity analysis using Sobol's method and an example decision support tool.
- Characterization of the context for a decision-making problem using network properties and traffic demand.

- Development of a framework for a meta model for selecting an appropriate decision support tool for a given context.
- Selection and application of machine learning algorithms to support the application of the meta model to a case study.

7.4 Future Work

Finally, future work based on the concepts demonstrated in this dissertation can be explored. The future work falls into two categories. The first is the generalization of this case-based research. The second is the exploration of other methods.

As this is case-based research, additional research can involve other contexts and other decision-support tools. For example:

- The variance-based sensitivity analysis applied to the case study TAM decision tool can be used to explore the sensitivity of alternative input data, and the application of global sensitivity analysis to other TAM decision support tools to determine if similar findings will be obtained. The methods can also be applied to different and larger networks. Such findings can help simplify models or direct attention to particularly influential parameters for specific infrastructure asset management problems by letting decision-makers focus more on the parameters that matter most.
- The meta-model framework can be applied to other decision support tools that are used by different highway agencies using actual input-output data, including realistic network structures where necessary, rather than simulated data as demonstrated in this dissertation.

- Alternative decision-making strategies also warrant further exploration. In this research, 1000 simulations were used to reflect alternative condition states based on Markov deterioration models. The optimal policy was selected using the average of the costs obtained from the simulation, and the meta-model selects the preferred tool for a scenario based on these average values. It is possible that the distribution of the costs is such that the lowest mean has very high variance but a near optimal mean has a much lower variance suggesting that the latter could be desirable in some instances. Therefore, some attention should be paid to variance and the influence of extreme values or outliers.

This dissertation selected methods that demonstrated the concepts of global sensitivity analysis and the meta models. Future research can explore:

- Alternative methods for global sensitivity analysis, such as those described in Ge et al. (2014), that address some of the concerns regarding the computational intensity of Sobol's method.
- Novel machine learning algorithms for the meta-model. While the algorithms used in this research are effective, new and emerging methods warrant exploration.

In summary, there are many opportunities for future research. These opportunities build on alternative and emerging methods and the models and data that are used by highway agencies. Ideally, a collaborative effort to build a meta-model that integrates all models, similar to FHWA's AIMS initiative could be launched.

REFERENCES

AASHTO. (n.d.). Multiple Objective Decision Analysis Tool (MODAT) Retrieved from https://multiobjective.org/web/about

AASHTO (2022). Highway capacity manual (7th ed.). Transportation Research Board.

Aderinlewo, O. O. (2008). Assessment of a transportation infrastructure system and its component interactions (Order No. 3324449). Available from Dissertations & Theses @ University of Delaware; ProQuest Dissertations & Theses Global, Retrieved from https://www.proquest.com/dissertations-theses/assessment-transportation-infrastructure-system/docview/304629707/se-2

Adey, B., Hajdin, R., & Brühwiler, E. (2004). Effect of common cause failures on indirect costs. Journal of Bridge Engineering, *9*(2), 200-208.

Ahmed, M. A., Kays, H. I., & Sadri, A. M. (2023). Centrality-based lane interventions in road networks for improved level of service: the case of downtown Boise, Idaho. Applied Network Science, 8(1), 2.

Alaloul, W. S., Altaf, M., Musarat, M. A., Faisal Javed, M., & Mosavi, A. (2021). Systematic review of life cycle assessment and life cycle cost analysis for pavement and a case study. Sustainability, 13(8), 4377.

Alhossen, I., Baudoin, F., Bugarin, F., Segonds, S., & Teyssèdre, G. (2019). Use of Sobol indexes for efficient parameter estimation in a charge transport model. IEEE Transactions on Dielectrics and Electrical Insulation, 26(2), 584-592.

Atolagbe, B., & McNeil, S. (2023a). Asset Management Decision Support Tools: Computational Complexity, Transparency, and Realism. Engineering Proceedings, 36(1), 5.

Atolagbe, B., & McNeil, S. (2023b). Identification of Key Model Parameters in an Infrastructure Decision Support Tool Using Sobol Sensitivity Method. *ASCE* International Conference on Transportation & Development, Austin TX, June.

Atolagbe, B., & McNeil, S. (2023c). Transportation Asset Management Decision Support Tools: Computational Complexity, Transparency, and Realism. Infrastructures, 8(10), 143.

Atolagbe, B., & McNeil, S. (2024a). Developing Meta Data for State DOTs from Complex Optimization Problems to Support Asset Management. Final Report Center for Integrated Asset Management for Multimodal Transportation.

Atolagbe, B., & McNeil, S. (2024b). What do local and global sensitivity analysis tell us about asset management decision support tools? Submitted to Transportation Research Record.

Attoh-Okine, N. O. (2017). Big data and differential privacy: analysis strategies for railway track engineering: John Wiley & Sons.

Balogun, I., & Attoh-Okine, N. (2021). Random Forest–Based Covariate Shift in Addressing Nonstationarity of Railway Track Data. ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering, 7(3), 04021028.

Batouli, M., Mostafavi, A., & Chowdhury, A. G. (2022). DyNet-LCCA: a simulation framework for dynamic network-level life-cycle cost analysis in evolving infrastructure systems. Sustainable and Resilient Infrastructure, 7(2), 112-129.

Baudoin, F., Le Roy, S., Teyssedre, G., Laurent, C., Alhossen, I., Bugarin, F., . . . Binaud, N. (2016). Parameters sensitivity analysis in charge transport model using Sobol indexes for optimization purpose. Paper presented at the 2016 IEEE International Conference on Dielectrics (ICD).

Bhamidipati, S. (2015). Simulation framework for asset management in climate-change adaptation of transportation infrastructure. Transportation Research Procedia, 8, 17-28.

Brackstone, M., Montanino, M., Daamen, W., Buisson, C., & Punzo, V. (2012). Use, calibration, and validation of traffic simulation models in practice: results of Web-based survey. Paper presented at the TRB 2012-Transportation Research Board 91rd Annual Meeting.

Branston, D. (1976). Link capacity functions: A review. Transportation research, 10(4), 223-236.

California Department of Transportation. (2018). California Transportation Asset Management Plan Fiscal Years 2017/18 - 2026/27. Retrieved from https://www.tamptemplate.org/wp-content/uploads/tamps/033_california.pdf. Retrieved March 3, 2023

Chen, L., & Bai, Q. (2019). Optimization in decision making in infrastructure asset management: A review. Applied Sciences, 9(7), 1380.

Das, T., Goerlandt, F., & Tabri, K. (2022). An optimized metamodel for predicting damage and oil outflow in tanker collision accidents. Proceedings of the Institution of Mechanical Engineers, Part M: Journal of Engineering for the Maritime Environment, 236(2), 412-426.

De Jong, G., Gunn, H., & Ben-Akiva, M. (2004). A meta-model for passenger and freight transport in Europe. Transport Policy, 11(4), 329-344.

Dehghani, M. S., Giustozzi, F., Flintsch, G. W., & Crispino, M. (2013). Cross-asset resource allocation framework for achieving performance sustainability. Transportation research record, 2361(1), 16-24.

Delaware Department of Transportation. (2019). Transportation Asset Management Plan. Retrieved from https://deldot.gov/Publications/tamp/pdfs/DelDOT-Transportation-Asset-Management-Plan.pdf. Retrieved on March 3, 2023

Delaware Department of Transportation. (2023a). Delaware Road Inventory 2.0. ArcGIS. Retrieved from https://www.arcgis.com/home/item.html?id=445d6a18b20144a2bbbb8ba2e92f8ed0 Retrieved on January 16, 2025

Delaware Department of Transportation. (2023b). Delaware Vehicle Volume Summary 2023 (Traffic Summary). Retrieved from

https://deldot.maps.arcgis.com/apps/webappviewer/index.html?id=4f76a1fa5b5c493cb3e1fad44a50dad1 Retrieved on January 16, 2025

Dowd, Z., Franz, A. Y., & Wasek, J. S. (2018). A decision-making framework for maintenance and modernization of transportation infrastructure. IEEE Transactions on Engineering Management, 67(1), 42-53.

Dubitzky, W., Wolkenhauer, O., Cho, K.-H., & Yokota, H. (2013). Encyclopedia of systems biology (Vol. 402): Springer New York, NY, USA:.

Dueñas-Osorio, L. A. (2005). Interdependent response of networked systems to natural hazards and intentional disruptions: Georgia Institute of Technology.

Ek, B., VerSchneider, C., & Narayan, D. A. (2015). Global efficiency of graphs. AKCE International Journal of Graphs and Combinatorics, 12(1), 1-13.

Faddoul, R., Raphael, W., Soubra, A.-H., & Chateauneuf, A. (2013). Incorporating Bayesian networks in Markov decision processes. Journal of infrastructure systems, 19(4), 415-424.

Ferry, T. A., Delorit, J. D., & Chini, C. M. (2022). Infrastructure Decision-Making under Climate Change Uncertainty: Case Study of Centralized Heating at Wright-Patterson AFB, Ohio. Journal of infrastructure systems, 28(1), 05021011.

FHWA. (2023a). Analysis, Modeling, and Simulation Overview. Retrieved from https://highways.dot.gov/research/operations/analysis-modeling-simulation/analysis-modeling-simulation-overview Retrieved on November 22, 2024

FHWA. (2023b). Development of a Transportation System Simulation Manual (TSSM) (Ongoing). Retrieved from https://highways.dot.gov/research/operations/analysis-modeling-simulation/ams-projects#Development-Transportation-System-Simulation Retrieved on November 22, 2024

FHWA. (2025). Asset Management Overview. Retrieved from https://www.fhwa.dot.gov/asset/if08008/amo_02.cfm Retrieved on January 14, 2025

Frank, M., & Wolfe, P. (1956). An algorithm for quadratic programming. Naval research logistics quarterly, 3(1-2), 95-110.

Fwa, T., Chan, W., & Tan, C. (1996). Genetic-algorithm programming of road maintenance and rehabilitation. Journal of Transportation Engineering, 122(3), 246-253.

Gan, Y., Duan, Q., Gong, W., Tong, C., Sun, Y., Chu, W., . . . Di, Z. (2014). A comprehensive evaluation of various sensitivity analysis methods: A case study with a hydrological model. Environmental modelling & software, 51, 269-285.

Gareth, J., Daniela, W., Trevor, H., & Robert, T. (2013). An introduction to statistical learning: with applications in R: Spinger.

Gatel, L., Lauvernet, C., Carluer, N., Weill, S., & Paniconi, C. (2019). Sobol global sensitivity analysis of a coupled surface/subsurface water flow and reactive solute transfer model on a real hillslope. Water, 12(1), 121.

Ge, Q., Ciuffo, B., & Menendez, M. (2014). An exploratory study of two efficient approaches for the sensitivity analysis of computationally expensive traffic simulation models. IEEE Transactions on Intelligent Transportation Systems, 15(3), 1288-1297.

Georgia Department of Transportation. (2019). Transportation Asset Management Plan. Retrieved from https://www.dot.ga.gov/GDOT/Pages/TAM.aspx. Retrieved on March 3, 2023

Géron, A. (2022). Hands-on machine learning with Scikit-Learn, Keras, and TensorFlow: " O'Reilly Media, Inc.".

Golbeck, J. (2013). Analyzing the social web: Newnes.

Gong, G., Lv, W., Gao, G., & Wang, Q. (2023). Capacity-based identification of key nodes in urban road networks. Paper presented at the 2023 3rd International Conference on Consumer Electronics and Computer Engineering (ICCECE).

Haas, R., Hudson, W. R., & Zaniewski, J. P. (1994). Modern pavement management: Krieger Publishing Company, Malabar.

Haritha, P., & Anjaneyulu, M. (2023). Comparison of topological functionality-based resilience metrics using link criticality. Reliability Engineering & System Safety, 109881.

Hastie, T., Tibshirani, R., & Friedman, J. (2017). The elements of statistical learning: data mining, inference, and prediction. In: Springer.

Háznagy, A., Fi, I., London, A., & Nemeth, T. (2015). Complex network analysis of public transportation networks: A comprehensive study. Paper presented at the 2015 International Conference on Models and Technologies for Intelligent Transportation Systems (MT-ITS).

Henry, E., Furno, A., & Faouzi, N.-E. E. (2021). Approach to quantify the impact of disruptions on traffic conditions using dynamic weighted resilience metrics of transport networks. Transportation research record, 2675(4), 61-78.

Herman, J., & Usher, W. (2017). SALib: An open-source Python library for sensitivity analysis. Journal of Open Source Software, 2(9), 97.

Hooks, E. M., McNeil, S., Lattanzi, D., Papakonstantinou, K., Stoffels, S., Zhou, W., . . . Withers, A. (2021). Strategic Prioritization and Planning of Multi-Asset Transportation Infrastructure Maintenance, Rehabilitation, and Improvements: Phase 1–Prioritization through Optimization.

Huang, W., Zhang, X., Cheng, H., & Xie, J. (2023). Metamodel-Based Optimization Method for Traffic Network Signal Design under Stochastic Demand. Journal of Advanced Transportation, 2023(1), 3917657.

Huang, Z., Hale, D. K., Shladover, S. E., Lu, X.-Y., Liu, H., Li, Q., . . . Hosseini, M. (2021). Developing Analysis, Modeling, and Simulation Tools for Connected and Automated Vehicle Applications (FHWA-HRT-21-077). Retrieved from https://rosap.ntl.bts.gov/view/dot/57956

Hyari, K. H., Shatarat, N., & Khalafallah, A. (2017). Handling risks of quantity variations in unit-price contracts. Journal of construction engineering and management, 143(10), 04017079.

Iooss, B., & Lemaître, P. (2015). A review on global sensitivity analysis methods. Uncertainty management in simulation-optimization of complex systems: algorithms and applications, 101-122.

Judd, S. (2010). The MBR book: principles and applications of membrane bioreactors for water and wastewater treatment: Elsevier.

Lasisi, A. (2019). Dimension reduction techniques in track geometry quality analysis and safety (Order No. 27542421). Available from Dissertations & Theses @ University of Delaware; ProQuest Dissertations & Theses Global, Retrieved from https://www.proquest.com/dissertations-theses/dimension-reduction-techniques-track-geometry/docview/2544928124/se-2

Levinson, H. S., & Lomax, T. J. (1996). Developing a travel time congestion index. Transportation research record, 1564(1), 1-10.

Lin, M.-H., Tsai, J.-F., & Yu, C.-S. (2012). A review of deterministic optimization methods in engineering and management. Mathematical Problems in Engineering, 2012.

Mamdoohi, S., & Miller-Hooks, E. (2022). Machine Learning and Reverse Methods for a Deeper Understanding of Public Roadway Improvement Action Impacts during Execution. Journal of Advanced Transportation, 2022.

Marsland, S. (2011). Machine learning: an algorithmic perspective: Chapman and Hall/CRC.

Medury, A., & Madanat, S. (2013). Incorporating network considerations into pavement management systems: A case for approximate dynamic programming. Transportation Research Part C: Emerging Technologies, 33, 134-150.

Meijer, J., Harvey, J., Butt, A., Kim, C., Ram, P., Smith, K., & Saboori, A. (2021). LCA Pave: A Tool to Assess Environmental Impacts of Pavement Material and Design Decisions-Underlying Methodology and Assumptions (FHWA-HIF-22-033). Retrieved from https://rosap.ntl.bts.gov/view/dot/62728

Meneses, S., & Ferreira, A. (2013). Pavement maintenance programming considering two objectives: maintenance costs and user costs. International Journal of Pavement Engineering, 14(2), 206-221.

Mishalani, R. G., & Olayé, R. A. (1999). Sensitivity of long-term infrastructure condition to initial quality. Journal of infrastructure systems, 5(4), 143-149.

Montgomery, D. C., Runger, G. C., & Hubele, N. F. (2009). Engineering statistics: John Wiley & Sons.

Mount, J., & Zumel, N. (2019). Practical data science with R: Simon and Schuster.

Moylan, E. (2023). Traffic Assignment for Bigger Networks. Class Notes CE392C, University of Sydney.

Myles, A. J., Feudale, R. N., Liu, Y., Woody, N. A., & Brown, S. D. (2004). An introduction to decision tree modeling. Journal of Chemometrics: A Journal of the Chemometrics Society, 18(6), 275-285.

Negrin, I., Kripka, M., & Yepes, V. (2023). Metamodel-assisted design optimization in the field of structural engineering: A literature review. Structures, 52, 609-631.

Noldus, R., & Van Mieghem, P. (2015). Assortativity in complex networks. Journal of Complex Networks, 3(4), 507-542.

North Carolina Department of Transportation. (2019). NCDOT Transportation Asset Management Plan 2019 Final Report. Retrieved from https://connect.ncdot.gov/resources/Asset-Management/TAMP/Final%20TAMP%20-%20June%202021.pdf. Retrieved March on 3, 2023

Patwary, A. U., Huang, W., & Lo, H. K. (2021). Metamodel-based calibration of large-scale multimodal microscopic traffic simulation. Transportation Research Part C: Emerging Technologies, 124, 102859.

Pennsylvania Department of Transportation. (2019). PennDOT Transportation Asset Management Plan 2019. Retrieved from https://www.penndot.pa.gov/ProjectAndPrograms/Asset-

Management/Documents/PennDOT-TAMP.pdf. Retrieved on March 3, 2023

Promsuwan, P., Nakayama, S., Yamaguchi, H., & Kobayashi, S.-i. (2023). Topology Change Study of Urban Railway Networks in Bangkok Metropolitan Area for Node-Based Centralities and Link-Based Vulnerabilities View. Available at SSRN 4476235. Retrieved from https://ssrn.com/abstract=4476235

Purnawan, & Alfathira, R. (2023). Development of Traffic Delay and Queue Metamodel on Landslide Zone Based on Simulation Using VISSIM. Paper presented at the IOP Conference Series: Earth and Environmental Science.

Reed, P., Hadjimichael, A., Malek, K., Karimi, T., Vernon, C. R., Srikrishnan, V. A., . . . Keller, K. (2022). Addressing uncertainty in multisector dynamics research (PNNL-SA-166911). Retrieved from https://www.osti.gov/biblio/2426846

Ren, X., Zhang, Z., & Yu, Z. (2023). Analysis of the Complex Characteristics of the New York City Subway Network. Highlights in Science, Engineering and Technology, 64, 99-106.

Saltelli, A. (2002). Making best use of model evaluations to compute sensitivity indices. Computer physics communications, 145(2), 280-297.

Saltelli, A., Annoni, P., Azzini, I., Campolongo, F., Ratto, M., & Tarantola, S. (2010). Variance based sensitivity analysis of model output. Design and estimator for the total sensitivity index. Computer physics communications, 181(2), 259-270.

Saltelli, A., Tarantola, S., Campolongo, F., & Ratto, M. (2004). Sensitivity analysis in practice: a guide to assessing scientific models (Vol. 1): Wiley Online Library.

Schraven, D., Hartmann, A., & Dewulf, G. (2011). Effectiveness of infrastructure asset management: challenges for public agencies. Built environment project and asset management.

Serdar, M. Z., Koç, M., & Al-Ghamdi, S. G. (2022). Urban transportation networks resilience: indicators, disturbances, and assessment methods. Sustainable Cities and Society, 76, 103452.

Shewmaker, P., Chrysanthopoulou, S. A., Iskandar, R., Lake, D., & Jutkowitz, E. (2022). Microsimulation model calibration with approximate Bayesian computation in R: a tutorial. Medical Decision Making, 42(5), 557-570.

Shi, T., Yan, L., Guo, H., & Ai, J. (2020). Automatic Detection for Reused Open Source Codes Based on Similarity Identification of Software Networks. Paper presented at the 2019 6th International Conference on Dependable Systems and Their Applications (DSA).

Sobol, I. M. (2001). Global sensitivity indices for nonlinear mathematical models and their Monte Carlo estimates. Mathematics and computers in simulation, 55(1-3), 271-280.

Song, Y., Thatcher, D., Li, Q., McHugh, T., & Wu, P. (2021). Developing sustainable road infrastructure performance indicators using a model-driven fuzzy spatial multi-criteria decision making method. Renewable and Sustainable Energy Reviews, 138, 110538.

Stamos, I. (2023). Transportation Networks in the Face of Climate Change Adaptation: A Review of Centrality Measures. Future Transportation, 3(3), 878-900.

Subrat Mahapatra, M. W., Eric Beckett,, & Sadabadi, K. F. (2015). 2015 Maryland State Highway Mobility Report. Retrieved from amazon.com/machine-learning/b?ie=UTF8&node=23557394011&ref=aloc_sea_go_131708152227_kwd-837712804550_ml Retrieved on November 22, 2024

Szell, M., Mimar, S., Perlman, T., Ghoshal, G., & Sinatra, R. (2022). Growing urban bicycle networks. Scientific reports, 12(1), 6765.

Taylor, M. (2017). Vulnerability analysis for transportation networks: Elsevier.

Umaisara Rashid, N., & Chan, K. T. (2023). A Review on Transportation Network based on Complex Network Approach. arXiv e-prints, arXiv: 2308.04636.

Valente, T. W. (2010). Social networks and health: Models, methods, and applications: Oxford University Press.

Van Werkhoven, K., Wagener, T., Reed, P., & Tang, Y. (2009). Sensitivity-guided reduction of parametric dimensionality for multi-objective calibration of watershed models. Advances in Water Resources, 32(8), 1154-1169.

Wang, G. G., & Shan, S. (2006). Review of metamodeling techniques in support of engineering design optimization. Paper presented at the International Design Engineering Technical Conferences and Computers and Information in Engineering Conference.

Wang, W., & Wu, Y. (2021). Is uncertainty always bad for the performance of transportation systems? Communications in transportation research, 1, 100021.

Wang, Y. N., Carrel, A. L., & Robert, W. (2021). Disaggregating Variability in Projected Benefits of Transit State of Good Repair Due to Uncertainty of Travel Demand Forecasts. Journal of Transportation Engineering, Part A: Systems, 147(11), 04021081.

Wang, Z., & Pyle, T. (2019). Implementing a pavement management system: The Caltrans experience. International Journal of Transportation Science and Technology, 8(3), 251-262.

Wei, C., & Tighe, S. (2004). Development of preventive maintenance decision trees based on cost-effectiveness analysis: an Ontario case study. Transportation research record, 1866(1), 9-19.

Xie, H.-y., Qin, C.-y., Zhi, P., Dong, Y.-b., & Li, J. (2023). Metamodel-Based Calibration of Microscopic Traffic Simulation: A Vissim Case Study. Journal of Highway and Transportation Research and Development (English Edition), 17(4), 49-58.

Xu, X., Chen, A., Jansuwan, S., Yang, C., & Ryu, S. (2018). Transportation network redundancy: Complementary measures and computational methods. Transportation Research Part B: Methodological, 114, 68-85.

Zhang, X., & Gao, H. (2012). Determining an optimal maintenance period for infrastructure systems. Computer-Aided Civil and Infrastructure Engineering, 27(7), 543-554.

Zhang, X. Y., Trame, M. N., Lesko, L. J., & Schmidt, S. (2015). Sobol sensitivity analysis: a tool to guide the development and evaluation of systems pharmacology models. CPT: pharmacometrics & systems pharmacology, 4(2), 69-79.

Zhou, W., Miller-Hooks, E., Papakonstantinou, K. G., Stoffels, S., & McNeil, S. (2022). A Reinforcement Learning Method for Multiasset Roadway Improvement Scheduling Considering Traffic Impacts. Journal of Infrastructure Systems, 28(4), 04022033.

Zhou, X., & Lin, H. (2008). Local Sensitivity Analysis. In Shekhar, S., Xiong, H. (eds) Encyclopedia of GIS. Boston, MA: Springer.

Appendix A

TOY NETWORK CONFIGURATIONS

This appendix documents the configuration and properties of the ten toy networks used to generate the data for the meta-model. For each network, a figure (Figure A-1 through A-10) shows the network configuration (connectivity). Each node is labeled with a numerical value (1,2….) and each edge or link is labeled with a lowercase letter. For networks with more than 26 edges, a numerical value is added to the letter, for example, a1. Each network represents a single origin-destination pair, and these nodes are also labelled "O' and "D" respectively. A table (Table A-1 through A-10) is associated with each network (and its corresponding figure) documenting for each link the capacity, type of link (pavement or bridge), the length, and the number of lanes. For each network up to three different configurations of link capacities (designated X, Y, and Z) are presented (represented by rows in each table) and for each configuration, up to four levels of demand for most of the networks, except Network 5 which has up to eight levels of demand.

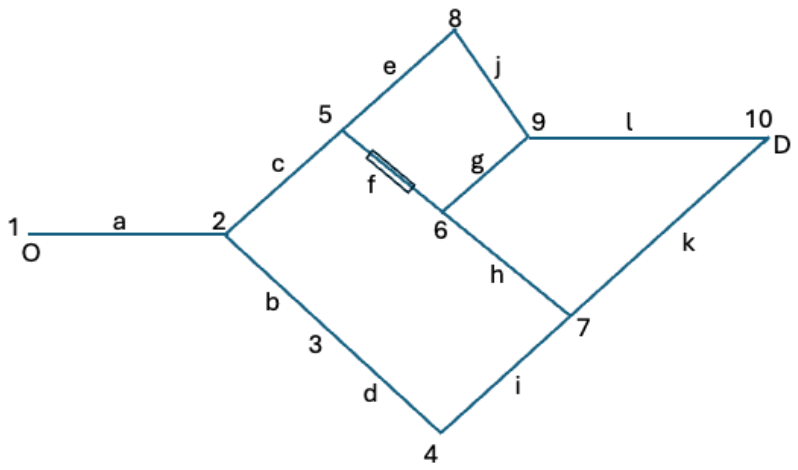


Figure A-1: Sketch of Network 1

Table A-1: Data for Network 1

Link ID	Properties				
	Capacity (000's veh/h)		Bridge (Yes=1)	Length (miles)	Lanes
	X	Y			
a	4	8	0	5	4
b	4	4	0	5	2
c	4	6	0	5	2
d	4	4	0	5	2
e	2	3	0	5	1
f	2	3	1	5	2
g	2	3	0	5	1
h	1	1.5	0	5	2
i	4	4	0	5	2
j	2	3	0	5	1
k	4	6	0	5	3
l	4	6	0	5	2
Demand (’000s veh/h)	2, 4, 5, 6, 7, 8	2, 4, 6, 8			

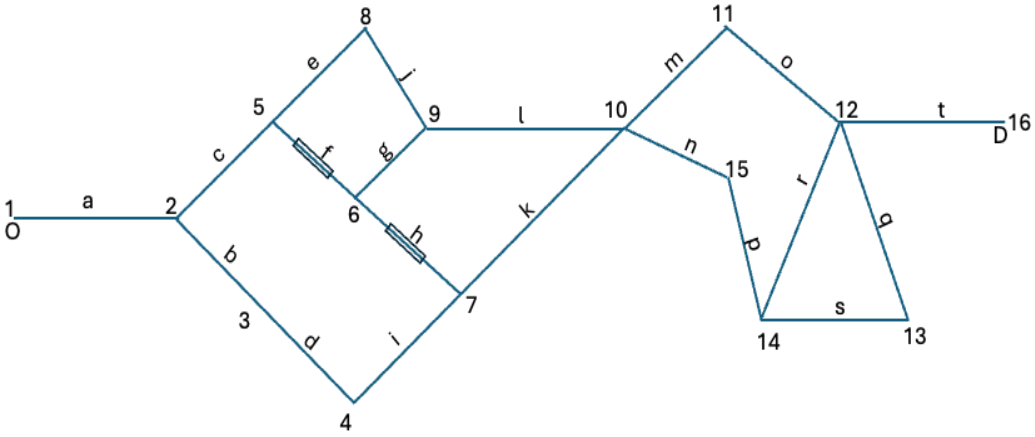


Figure A-2: Sketch of Network 2

Table A-2: Data for Network 2

Link ID	Properties					
	Capacity (000's veh/h)			Bridge (Yes=1)	Length (miles)	Lanes
	X	Y	Z			
a	8	8	8	0	5	4
b	4	4	6	0	5	2
c	4	4	2	0	5	2
d	4	4	4	0	5	2
e	2	2	2	0	5	1
f	4	2	4	1	5	1
g	2	2	2	0	5	1
h	4	2	2	1	5	1
i	4	4	2	0	5	2
j	2	2	4	0	5	1
k	6	4	2	0	5	3
l	4	2	2	0	5	1
m	4	4	4	0	5	2
n	4	4	2	0	5	2
o	4	4	4	0	5	2
p	4	4	4	0	5	2
q	4	4	4	0	5	2
r	4	2	4	0	5	1
s	4	4	4	0	5	2
t	8	8	8	0	5	4
Demand (’000s veh/h)	2, 4, 6, 8	2, 3, 6, 7	2, 4, 6, 8			

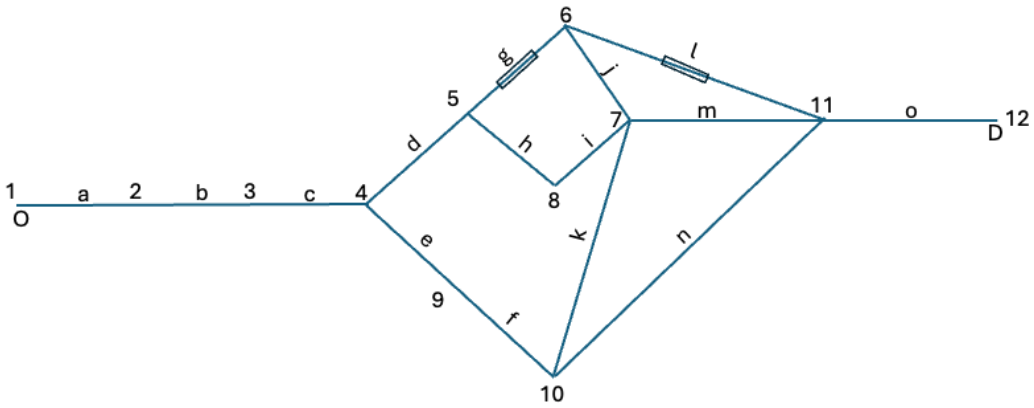


Figure A-3: Sketch of Network 3

Table A-3: Data for Network 3

Link ID	Properties					
	Capacity (000's veh/h)			Bridge (Yes=1)	Length (miles)	Lanes
	X	Y	Z			
a	8	8	8	0	5	4
b	8	8	8	0	5	4
c	8	8	8	0	5	4
d	4	3	4	0	5	2
e	4	5	4	0	5	2
f	4	5	4	0	5	2
g	2	1	2	1	5	1
h	2	2	2	0	5	1
i	2	2	2	0	5	1
j	2	1	1	0	5	1
k	4	2	2	0	5	2
l	2	1	2	1	5	1
m	2	1	1	0	5	1
n	4	5	2	0	5	2
o	8	8	8	0	5	4
Demand (’000s veh/h)	2, 3, 6, 8	2, 4, 6, 8	2, 4, 6, 8			

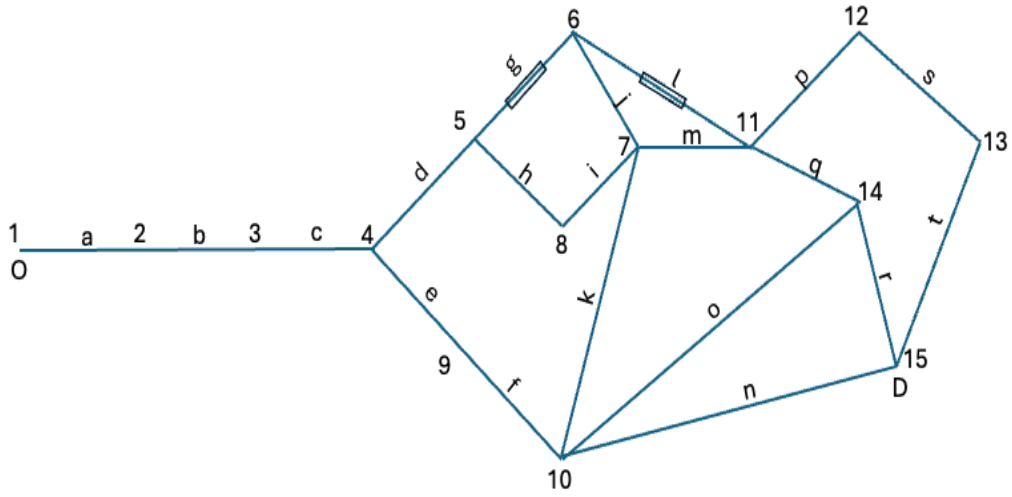


Figure A-4: Sketch of Network 4

Table A-4: Data for Network 4

Link ID	Properties					
	Capacity (000's veh/h)			Bridge (Yes=1)	Length (miles)	Lanes
	X	Y	Z			
a	8	8	8	0	5	4
b	8	8	8	0	5	4
c	8	8	8	0	5	4
d	8	4	4	0	5	2
e	8	4	2	0	5	2
f	8	4	2	0	5	2
g	8	4	4	1	5	1
h	8	4	4	0	5	1
i	8	4	4	0	5	1
j	8	4	4	0	5	1
k	8	4	4	0	5	1
l	8	4	4	1	5	1
m	8	4	4	0	5	2
n	8	4	2	0	5	2
o	8	4	4	0	5	2
p	8	8	8	0	5	2
q	8	8	8	0	5	2
r	8	8	8	0	5	2
s	8	8	8	0	5	2
t	8	8	8	0	5	2
Demand (’000s veh/h)	2, 4, 6, 8	2, 3, 6, 8	2, 4, 7			

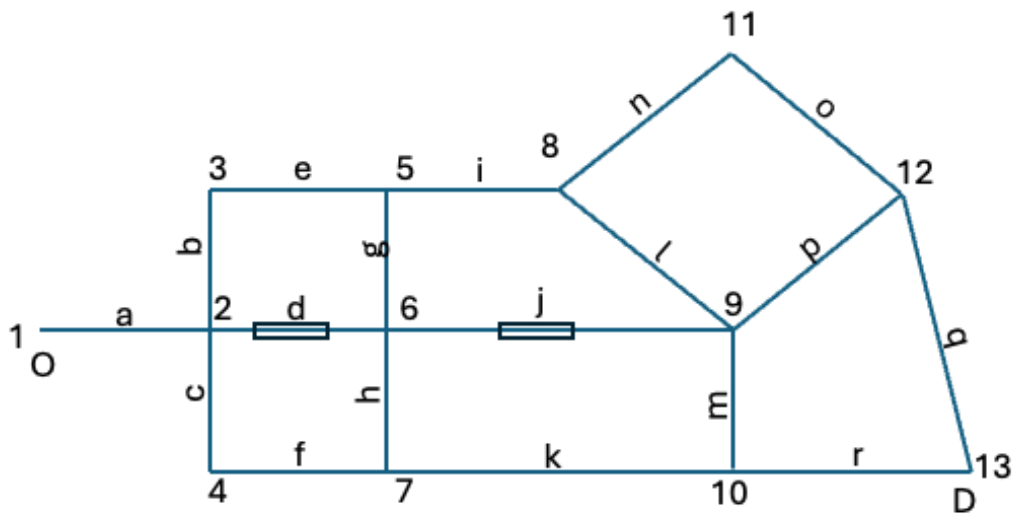


Figure A-5: Sketch of Network 5

Table A-5: Data for Network 5

Link ID	Properties			
	Capacity (000's veh/h) X	Bridge (Yes=1)	Length (miles)	Lanes
a	8	0	5	4
b	8	0	5	4
c	8	0	5	4
d	2	1	5	2
e	8	0	5	2
f	8	0	5	2
g	4	0	5	2
h	4	0	5	2
i	8	0	5	1
j	2	1	5	1
k	8	0	5	1
l	4	0	5	1
m	4	0	5	1
n	8	0	5	1
o	8	0	5	2
p	2	0	5	2
q	8	0	5	2
r	8	0	5	2
Demand (’000s veh/h)	1, 2, 3, 4, 5, 6, 7, 8			

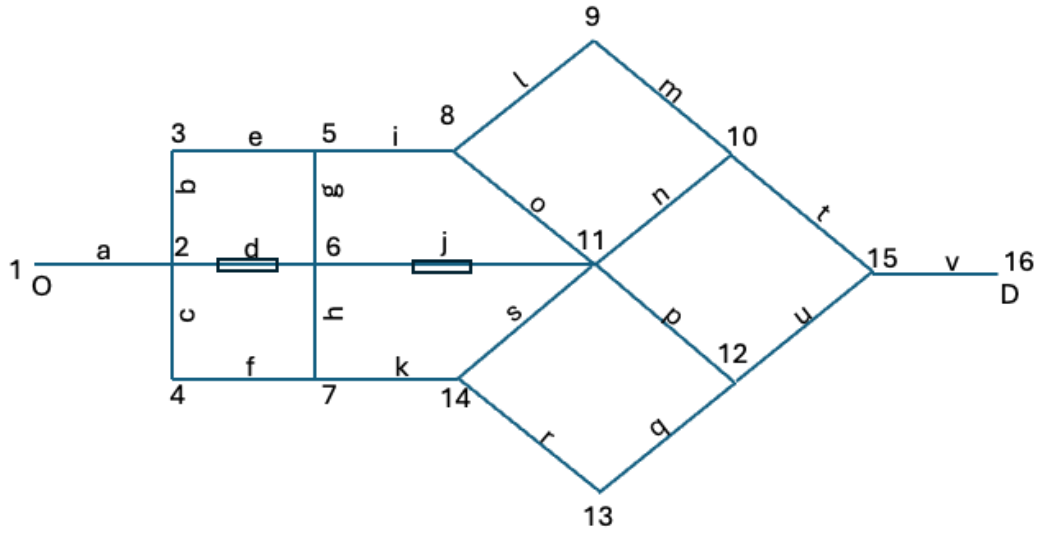


Figure A-6: Sketch of Network 6

Table A-6: Data for Network 6

Link ID	Properties					
	Capacity (000's veh/h)			Bridge (Yes=1)	Length (miles)	Lanes
	X	Y	Z			
a	8	8	8	0	5	4
b	8	4	4	0	5	4
c	8	4	4	0	5	4
d	8	4	2	1	5	2
e	8	4	4	0	5	2
f	8	4	4	0	5	2
g	8	4	4	0	5	2
h	8	4	4	0	5	2
i	8	4	4	0	5	1
j	8	4	4	1	5	1
k	8	4	4	0	5	1
l	8	4	4	0	5	1
m	8	4	4	0	5	1
n	8	4	4	0	5	1
o	8	4	4	0	5	1
p	8	4	2	0	5	2
q	8	4	4	0	5	2
r	8	4	4	0	5	2
s	8	4	4	0	5	2
t	8	4	4	0	5	2
u	8	4	2	0	5	2
v	8	8	8	0	5	2
Demand (’000s veh/h)	2, 4, 6, 8	2, 3, 6, 8	2, 4, 6, 8			

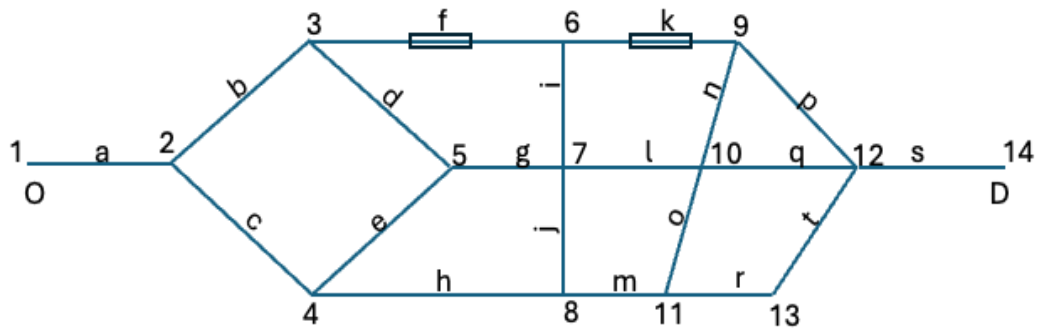


Figure A-7: Sketch of Network 7

Table A-7: Data for Network 7

Link ID	Properties					
	Capacity (000's veh/h)			Bridge (Yes=1)	Length (miles)	Lanes
	X	Y	Z			
a	8	8	8	0	5	4
b	8	8	8	0	5	4
c	8	8	8	0	5	4
d	8	4	4	0	5	2
e	8	4	4	0	5	2
f	8	4	2	1	5	2
g	8	4	4	0	5	2
h	8	4	4	0	5	2
i	8	4	4	0	5	1
j	8	4	4	0	5	1
k	8	4	2	1	5	1
l	8	4	4	0	5	1
m	8	4	4	0	5	1
n	8	4	4	0	5	1
o	8	4	4	0	5	1
p	8	4	2	0	5	2
q	8	4	4	0	5	2
r	8	4	4	0	5	2
s	8	8	8	0	5	2
t	8	4	4	0	5	2
Demand (’000s veh/h)	2, 4, 6, 8	2, 3, 6, 8	2, 4, 6, 8			

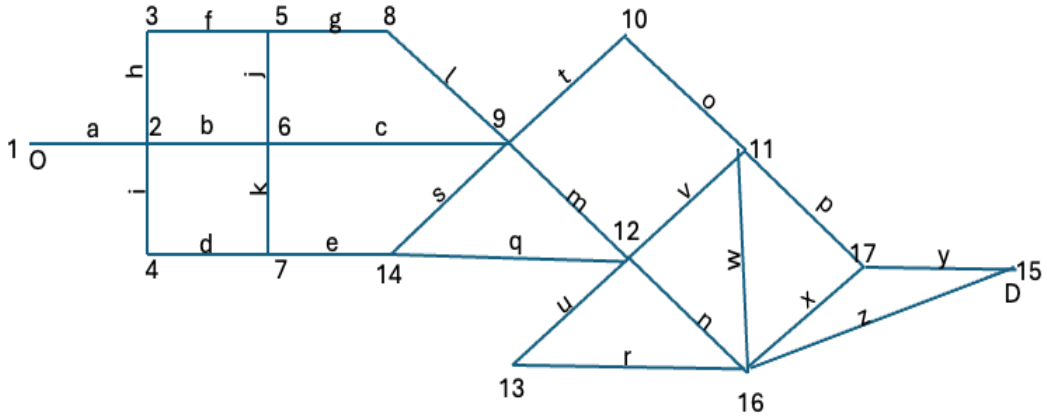


Figure A-8: Sketch of Network 8

Table A-8: Data for Network 8

Link ID	Properties			
	Capacity (000's veh/h) X	Bridge (Yes=1)	Length (miles)	Lanes
a	8	0	5	4
b	4	0	5	4
c	4	0	5	4
d	4	0	5	2
e	4	0	5	2
f	4	0	5	2
g	4	0	5	2
h	4	0	5	2
i	4	0	5	1
j	4	0	5	1
k	4	0	5	1
l	4	0	5	1
m	4	0	5	1
n	4	0	5	1
o	4	0	5	1
p	4	0	5	2
q	16	0	5	2
r	16	0	5	2
s	4	0	5	2
t	4	0	5	2
u	16	0	5	2
v	4	0	5	2
w	4	0	5	2
x	4	0	5	2
y	16	0	5	2
z	4	0	5	2
Demand (’000s veh/h)	2, 4 ,6			

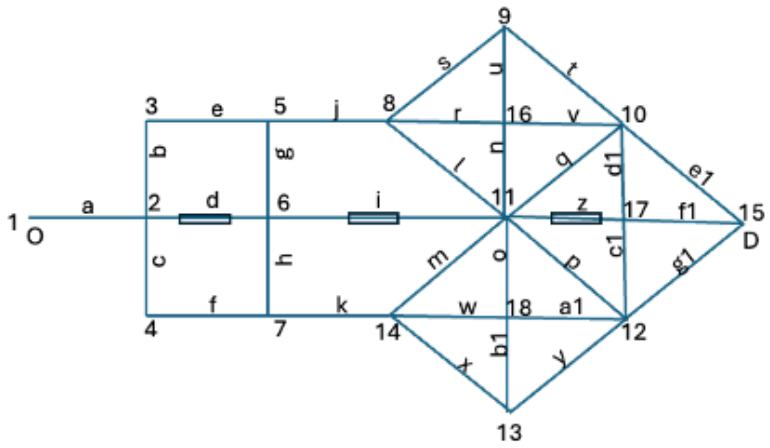


Figure A-9: Sketch of Network 9

Table A-9: Data for Network 9

Link ID	Properties				
	Capacity (000's veh/h)		Bridge (Yes=1)	Length (miles)	Lanes
	X	Y			
a	8	8	0	5	4
b	4	4	0	5	4
c	4	4	0	5	4
d	4	2	1	5	2
e	4	4	0	5	2
f	4	4	0	5	2
g	4	2	0	5	2
h	4	2	0	5	2
i	4	2	0	5	1
j	4	4	0	5	1
k	4	4	0	5	1
l	4	2	1	5	1
m	4	2	0	5	1
n	2	2	0	5	1
o	2	2	0	5	1
p	4	2	0	5	2
q	4	2	0	5	2
r	2	2	0	5	2
s	4	2	0	5	2
t	4	2	0	5	2
u	2	2	0	5	2
v	2	2	0	5	2
w	2	2	0	5	2
x	4	2	0	5	2
y	4	2	0	5	2
z	4	2	1	5	2
a1	2	2	0	5	2
b1	2	2	0	5	2
c1	2	2	0	5	2

d1	2	2	0	5	2
e1	4	4	0	5	2
f1	4	2	0	5	2
g1	4	4	0	5	2
Demand (’000s veh/h)	2, 4, 5, 7	2, 4, 6, 8			

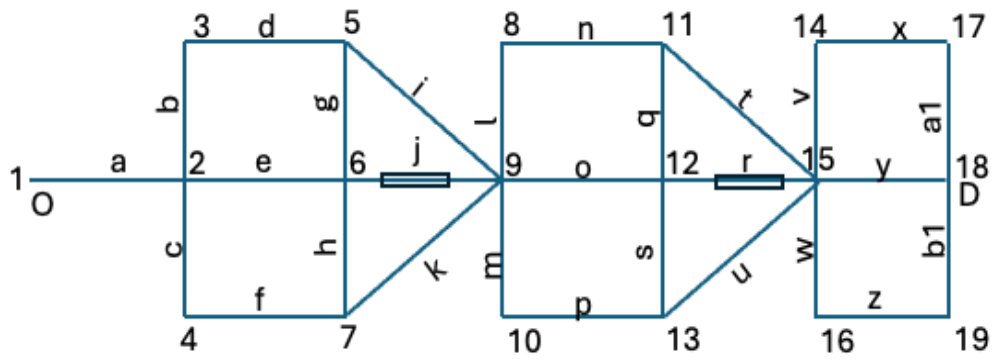


Figure A-10:Sketch of Network 10

Table A-10: Data for Network 10

Link ID	Properties					
	Capacity (000's veh/h)			Bridge (Yes=1)	Length (miles)	Lanes
	X	Y	Z			
a	8	8	8	0	5	4
b	8	8	8	0	5	4
c	8	8	8	0	5	4
d	8	8	8	0	5	2
e	8	4	2	0	5	2
f	8	8	8	0	5	2
g	8	8	8	0	5	2
h	8	8	8	0	5	2
i	8	8	8	0	5	1
j	8	4	2	1	5	1
k	8	8	8	0	5	1
l	8	8	8	0	5	1
m	8	8	8	0	5	1
n	8	8	8	0	5	1
o	8	4	2	0	5	1
p	8	8	8	0	5	2
q	8	8	8	0	5	2
r	8	4	2	1	5	2
s	8	8	8	0	5	2
t	8	8	8	0	5	2
u	8	8	8	0	5	2
v	8	8	8	0	5	2
w	8	4	2	1	5	2
x	8	8	8	0	5	2
y	8	8	8	0	5	2
z	8	8	8	0	5	2
a1	8	8	8	0	5	2
b1	8	8	8	0	5	2

Demand (’000s veh/h)	2, 4, 6, 8	2, 4, 5, 6	2, 4, 6, 8			

Appendix B

SUPPLEMENTARY FIGURES ON EXPLORATORY DATA ANALYSIS

This appendix includes boxplots (Figures B-1 to B-3) and histograms (Figures B-4 to B-6) for the total cost over the planning horizon for each of the case study models for traffic factors of 0.5, 0.75 and 1.0 to supplement the plots for a traffic factor of 0.25 presented in Figure 6.3 and Figure 6.5.

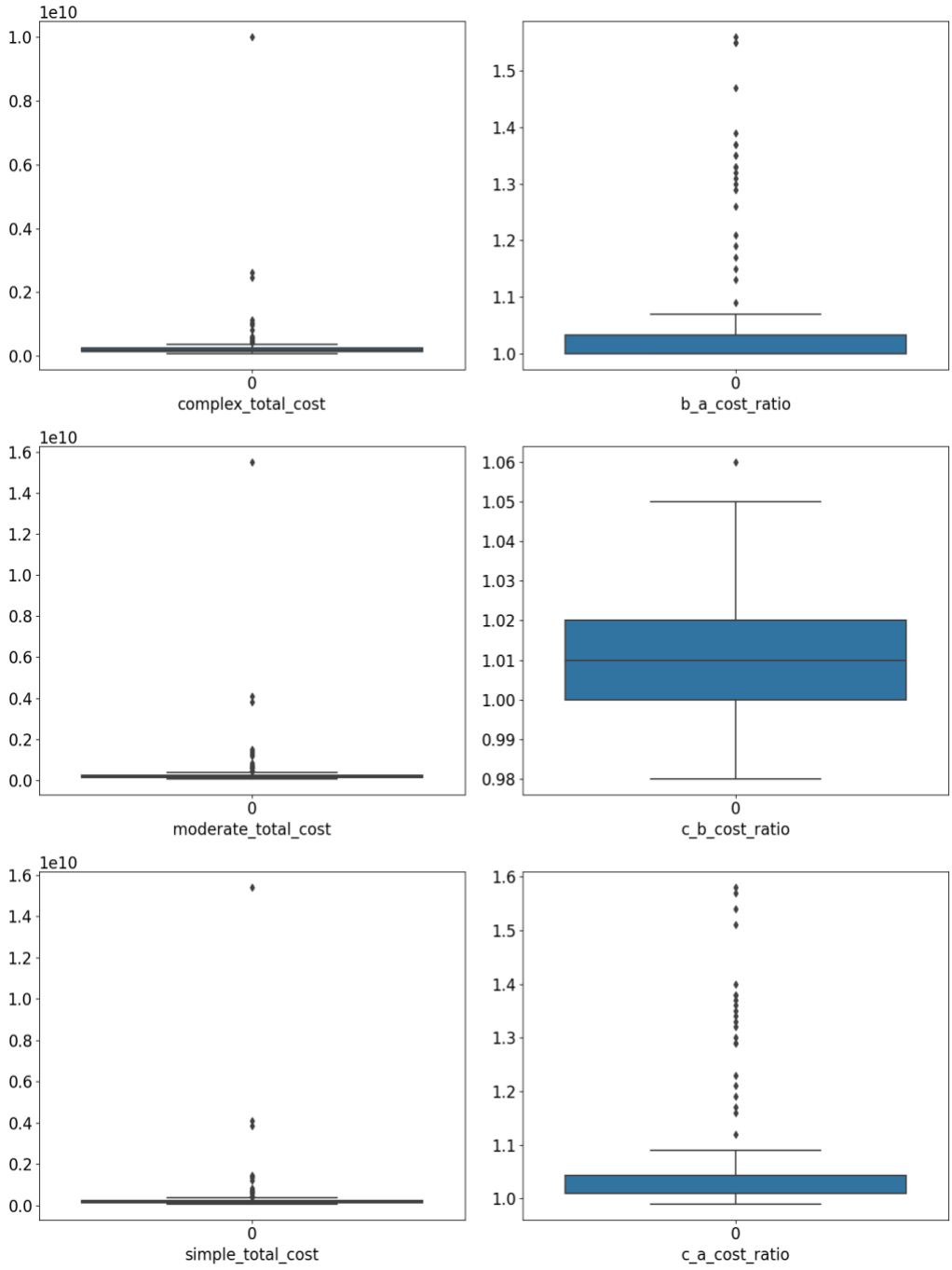


Figure B-1: Box and Whisker's plot of total cost (Traffic Factor= 0.50)

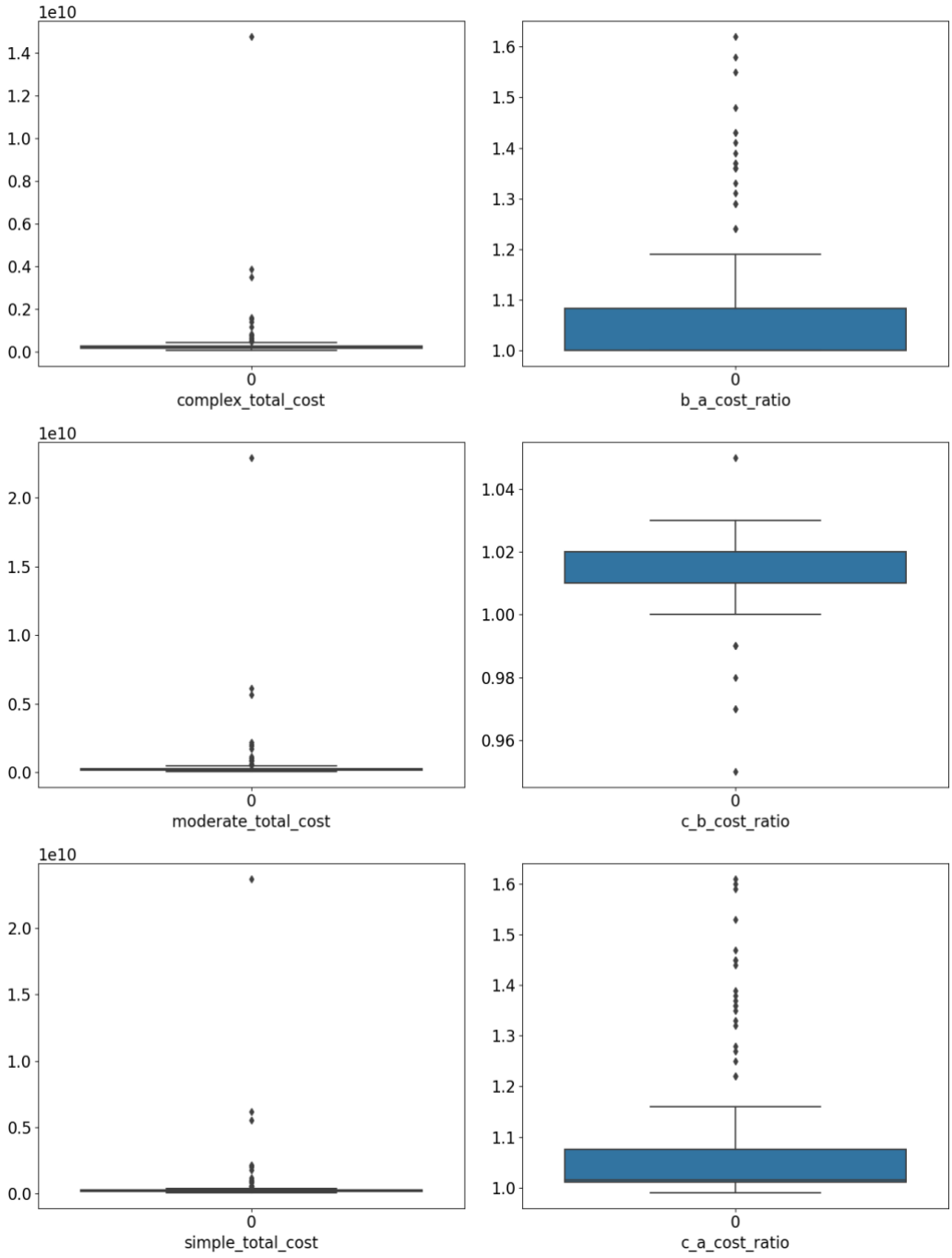


Figure B-2: Box and Whisker's Plot of total cost (Traffic Factor= 0.75)

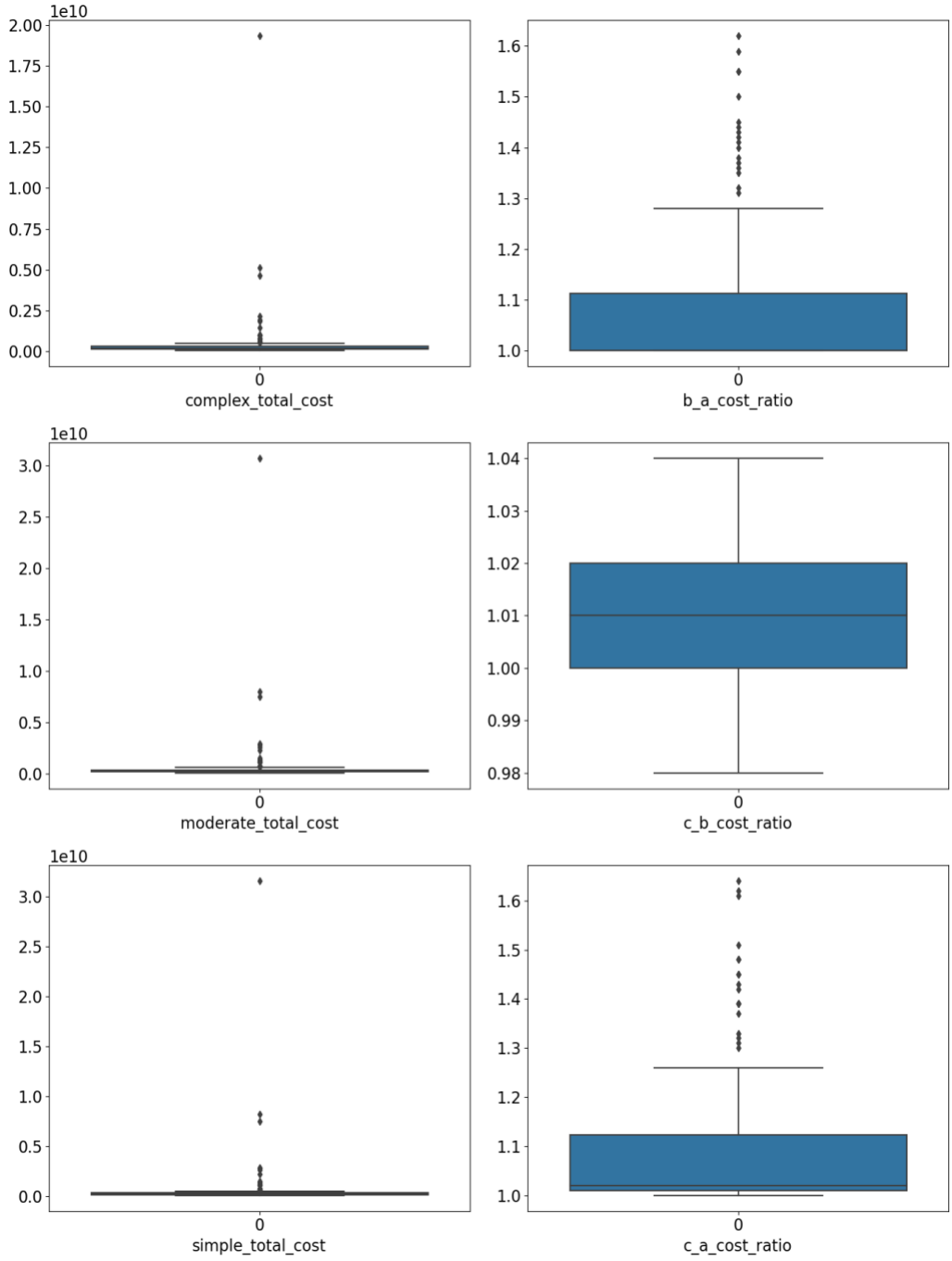


Figure B-3: Box and Whisker's Plot of total cost (Traffic Factor= 1.0)

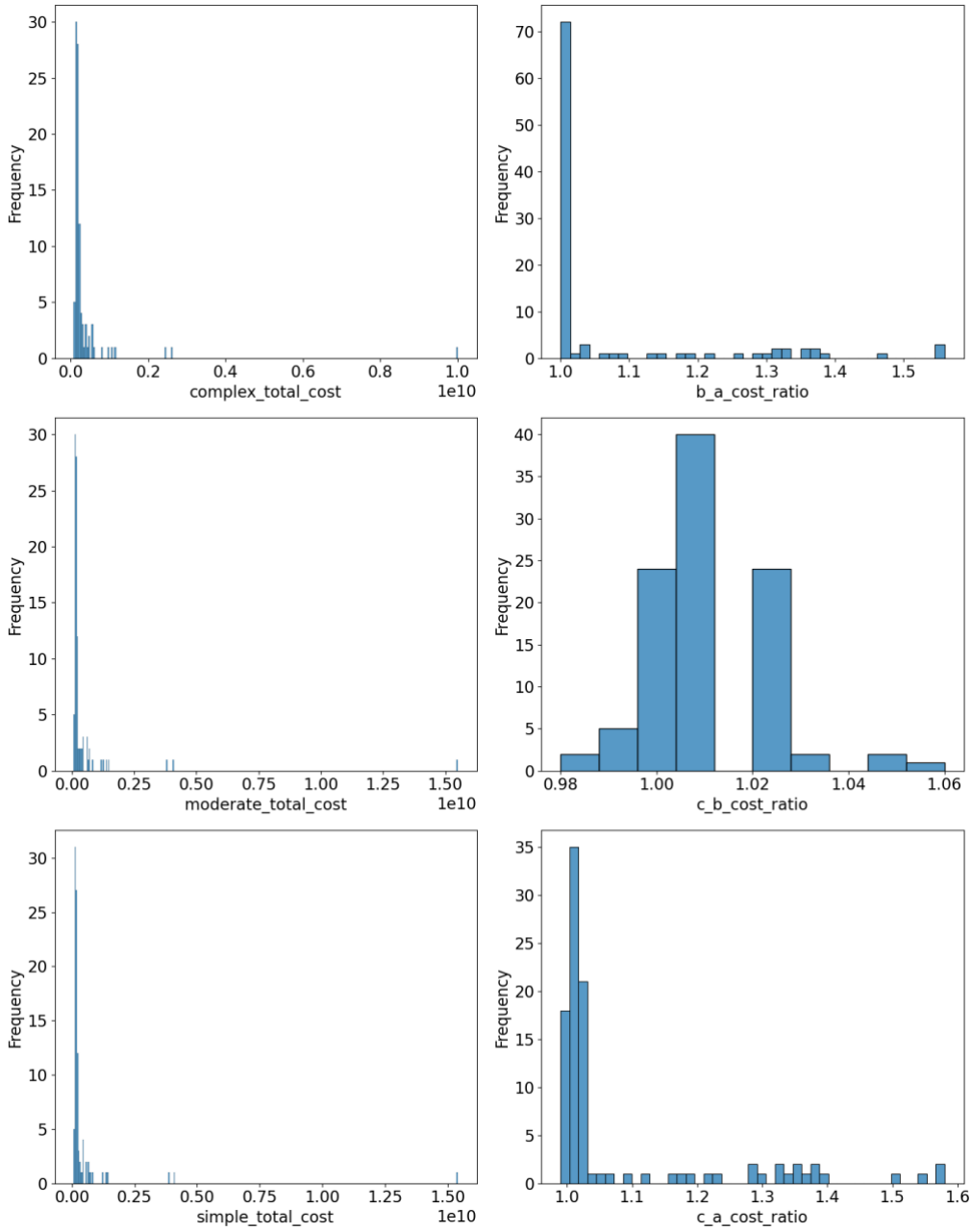


Figure B-4: Histograms of cost properties (Traffic Factor = 0.50)

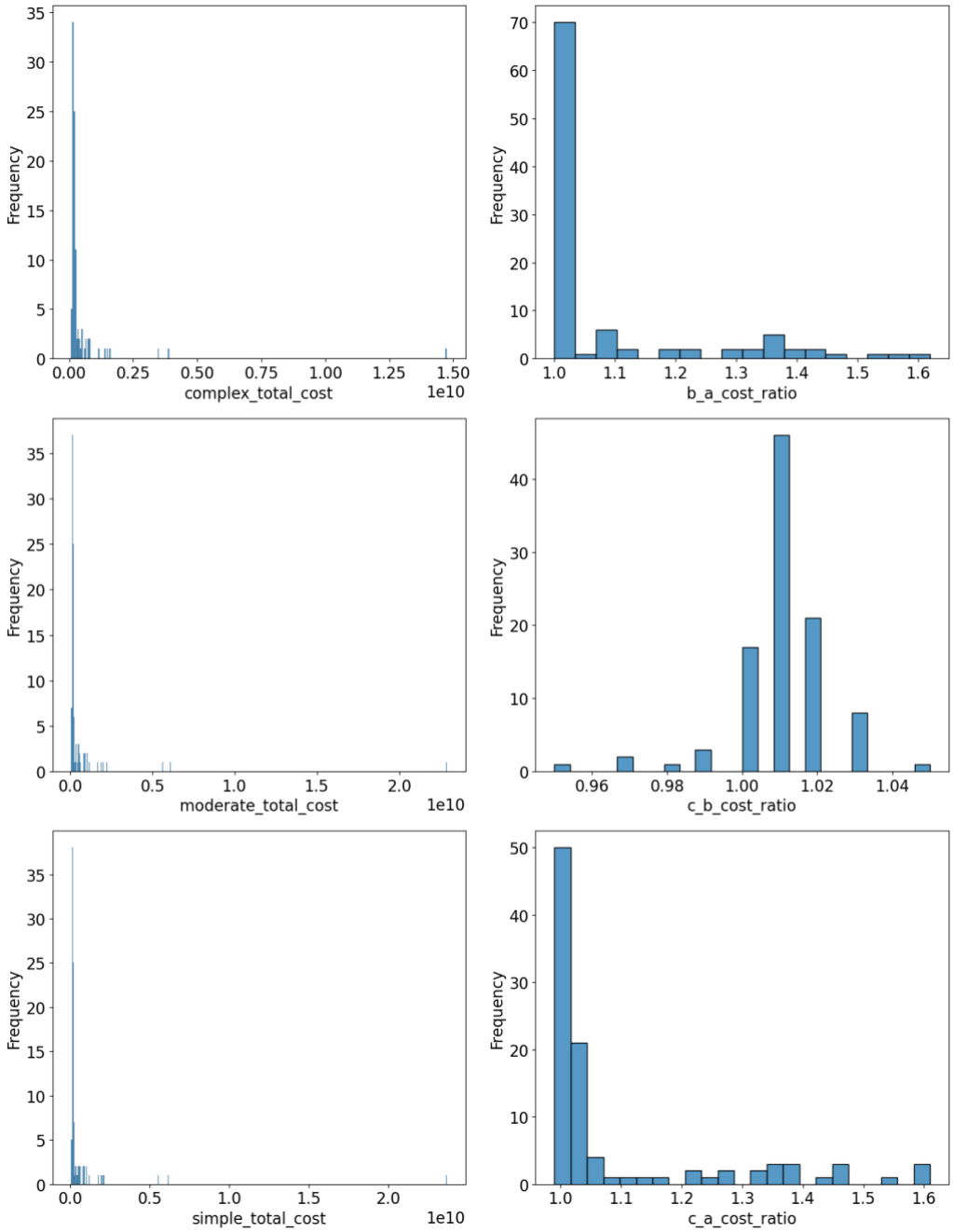


Figure B-5: Histograms of cost properties (Traffic Factor = 0.75)

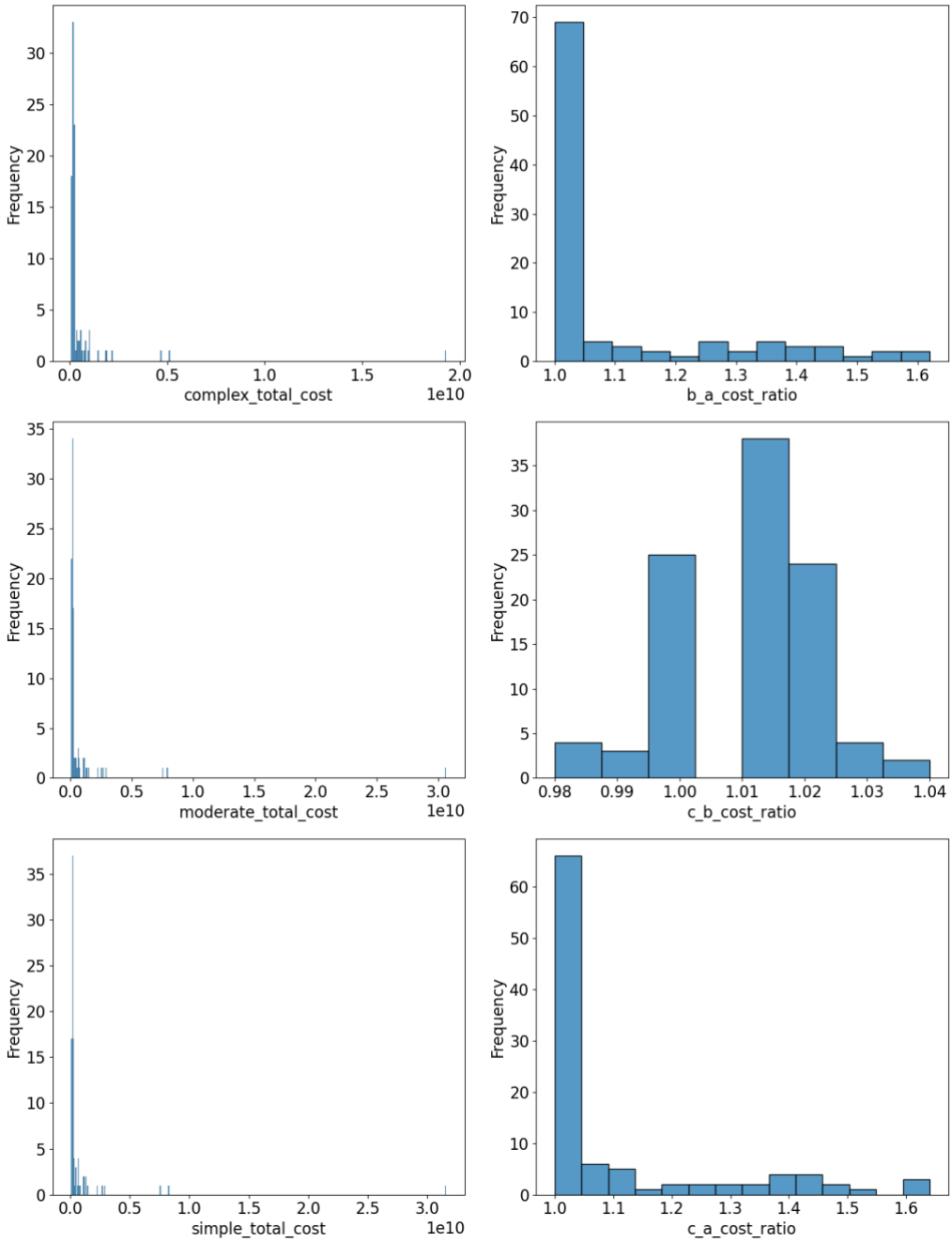


Figure B-6: Histograms of cost properties (Traffic Factor = 1.0)

Appendix C

APPLICATION TO A NETWORK BASED ON REAL-WORLD DATA

To show the application of the metamodel framework, an illustration is presented based on a small real-life network. The case-study network, Figure C-1, re-presented in Figure C-2, and idealized as shown in Figure C-3, consists of a section of I-95 highway in Newark, Delaware between DE 7 and DE 896, Delaware Route 1, Route 4, Route 7, Route 72, Route 273, Route 896, US 40, South Old Baltimore Road and Salem Church Road. The attributes of each link were obtained from the Delaware Road Inventory 2.0 repository (Delaware Department of Transportation, 2023a). These include number of lanes, length, lane width, speed, width of shoulder. Capacity of the segment is computed using $c = s \times phf \times N \times f_w \times f_h \times f_g$, where s is the base saturation flow rate, assumed as 2000 vehicle per hour (vph); phf is the peak hour factor, assumed as 1.0; N is the number of lanes; f_w, f_h and f_g are adjustment factors based on lane width, heavy vehicle proportion, and roadway grade respectively. f_h and f_g are assumed as 1.0 while f_w is determined according to (Highway Capacity Manual, 2022). The free flow travel time on each segment is computed as the ratio of the length of the link to the speed.

Assuming one Origin-Destination pair in the network to be consistent with the assumption made for developing the metamodel framework, the traffic demand on the network is estimated as the sum of the traffic entering the network at the east

end of I-95, including traffic traveling Southbound I-95, as well as Northbound and Southbound DE 7. The Annual Average Daily Traffic (AADT) for these links were obtained from the Delaware Department of Transportation 2023 Traffic Count (Delaware Department of Transportation, 2023b). The sum, averaged over a 24-hour period, is 15,450 vehicles per hour.

The life-cycle cost models, A (complex tool) and C (simple tool), were implemented using the described I-95 case-study network as input. Model parameters were set as follows: deterioration rate = 0.05, user cost rate = 1.0, maintenance cost rate = 1.0, discount rate = 0.05, and traffic factor = 1.0. The output total cost for the tool C (simple tool) is $220,891,515 while that for tool A (complex tool) is $218,749,359. The cost ratio is 1.01. Given this value is less than the threshold of 1.05 used for labeling the scenarios, the simple tool (C) can be chosen for this decision scenario based on the labeling rule discussed in Section 6.2.2. This selection process requires running the two tools to determine the right tool.

Alternatively, using the trained metamodel classification model, the network properties of the case-study network are computed and are used to predict the right tool. These properties are: average degree centrality (=0.16), average betweenness centrality (= 0.1), average closeness centrality (= 0.37), average edge centrality (= 0.09), average local clustering coefficient (= 0.03), average shortest path length (= 2.72), diameter (= 5), network density (= 0.16), degree assortativity (= -0.05), global efficiency (= 0.46), OD level (= 15,450), TTI (= 1.00), and traffic

factor (= 1.0). With this set of predictors, the chosen tool is Tool C (simple tool). This process does not require running any of the tools to determine the right tool.

Considering the runtime for the simple tool is under a minute while that for the complex tool is approximately 30 minutes, selecting the right tool for this scenario would have simply been done using the metamodel classification model rather than having to run both tools to figure that out, keeping in mind that the number of tools may be more than two in reality with each requiring varying levels of computational effort.

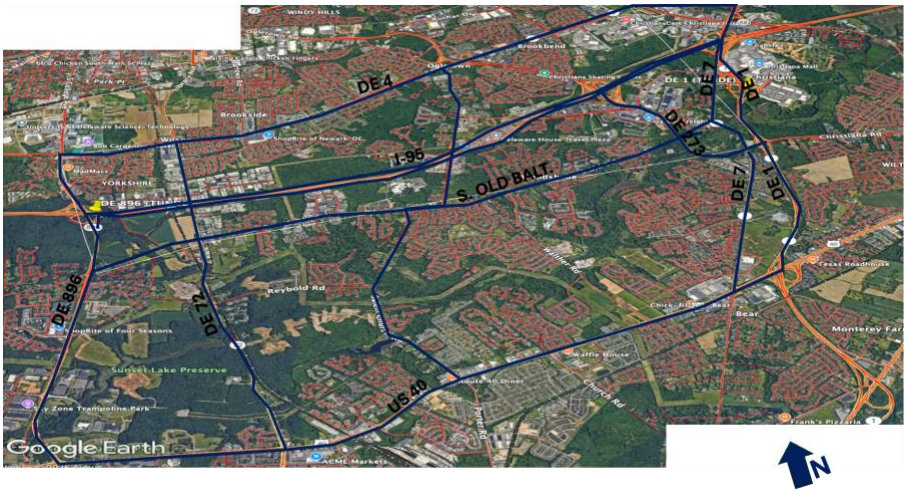


Figure C-1: Google Earth view of the case-study network in Newark, Delaware

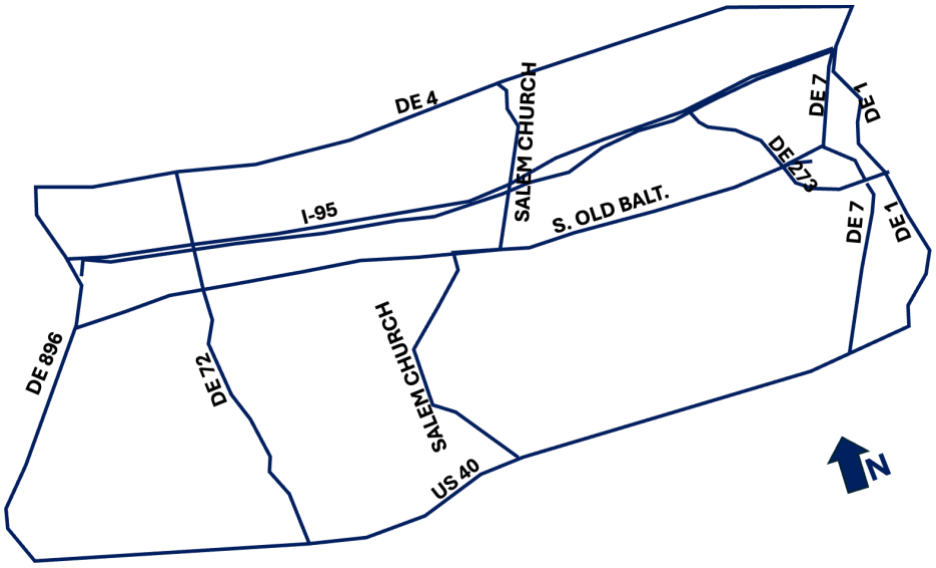


Figure C-2: Sketch of the case-study network

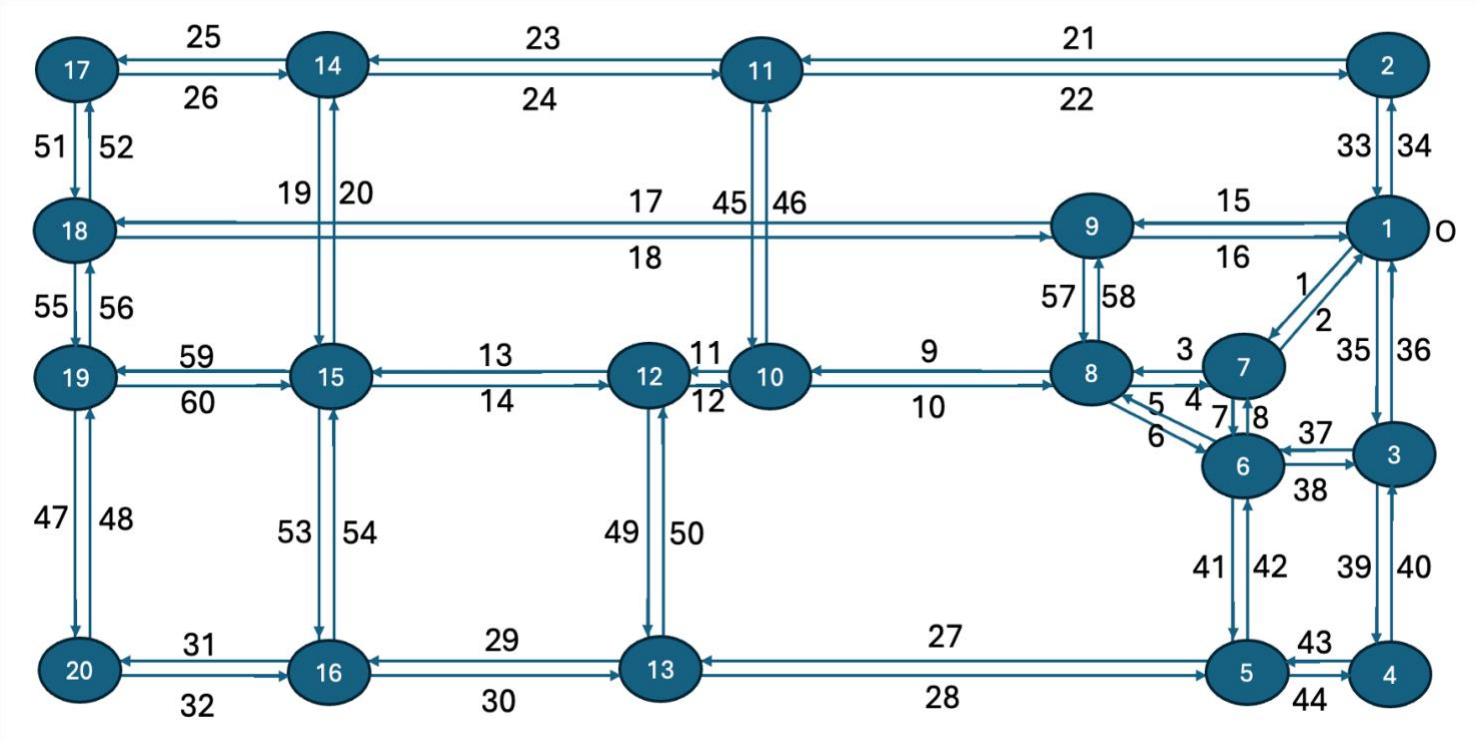


Figure C-3: Idealized graph representation of the case-study network

Table C-1: Link attributes for the case-study network

Link ID	Capacity (veh/hr)	Number of Lanes	Length (mile)	Width (ft/lane)	Speed (mph)	Freeflow Time (hr)
1	1960	1	1.34	11	35	0.04
2	2000	1	1.34	12	35	0.04
3	2000	1	0.31	12	45	0.01
4	2000	1	0.31	12	45	0.01
5	4000	2	0.66	12	50	0.01
6	4000	2	0.66	12	50	0.01
7	3920	2	0.49	11	45	0.01
8	3920	2	0.49	11	45	0.01
9	2000	1	2.03	13	45	0.05
10	2000	1	2.03	13	45	0.05
11	4000	2	0.28	13	45	0.01
12	4000	2	0.28	13	45	0.01
13	2000	1	1.49	13	45	0.03
14	2000	1	1.49	13	45	0.03
15	8000	4	1.40	12	65	0.02
16	8000	4	1.40	12	65	0.02
17	8000	4	4.27	12	65	0.07
18	8000	4	4.27	12	65	0.07
19	4000	2	1.34	12	45	0.03
20	4000	2	1.34	12	45	0.03
21	4000	2	2.92	12	45	0.06
22	4000	2	2.92	12	45	0.06
23	4000	2	2.40	12	50	0.05
24	4000	2	2.40	12	50	0.05
25	4000	2	0.89	12	50	0.02
26	3920	2	0.89	11	50	0.02
27	4000	2	1.83	12	50	0.04

28	4000	2	1.83	12	50	0.04
29	4000	2	1.36	12	50	0.03
30	4000	2	1.36	12	50	0.03
31	4000	2	1.38	12	55	0.03
32	4000	2	1.38	12	55	0.03
33	1960	1	0.91	11	35	0.03
34	1960	1	0.91	11	35	0.03
35	4000	2	1.59	12	45	0.04
36	4000	2	1.59	12	45	0.04
37	4000	2	0.15	12	50	0.00
38	4000	2	0.15	12	50	0.00
39	4000	2	1.74	12	45	0.04
40	3920	2	1.74	11	60	0.03
41	3920	2	1.90	11	45	0.04
42	3920	2	1.90	11	45	0.04
43	4000	2	0.43	12	50	0.01
44	4000	2	0.43	12	50	0.01
45	2000	1	2.02	12	35	0.06
46	2000	1	2.02	12	35	0.06
47	4000	2	2.92	12	50	0.06
48	4000	2	2.92	12	50	0.06
49	2000	1	2.29	12	35	0.07
50	2000	1	2.29	12	35	0.07
51	4000	2	0.88	12	35	0.03
52	4000	2	0.88	12	35	0.03
53	2000	1	2.46	12	50	0.05
54	2000	1	2.46	12	50	0.05
55	4000	2	0.88	12	50	0.02
56	4000	2	0.88	12	50	0.02
57	4000	2	0.92	12	50	0.02
58	4000	2	0.92	12	50	0.02
59	1840	1	0.83	10	35	0.02
60	1840	1	0.83	10	35	0.02

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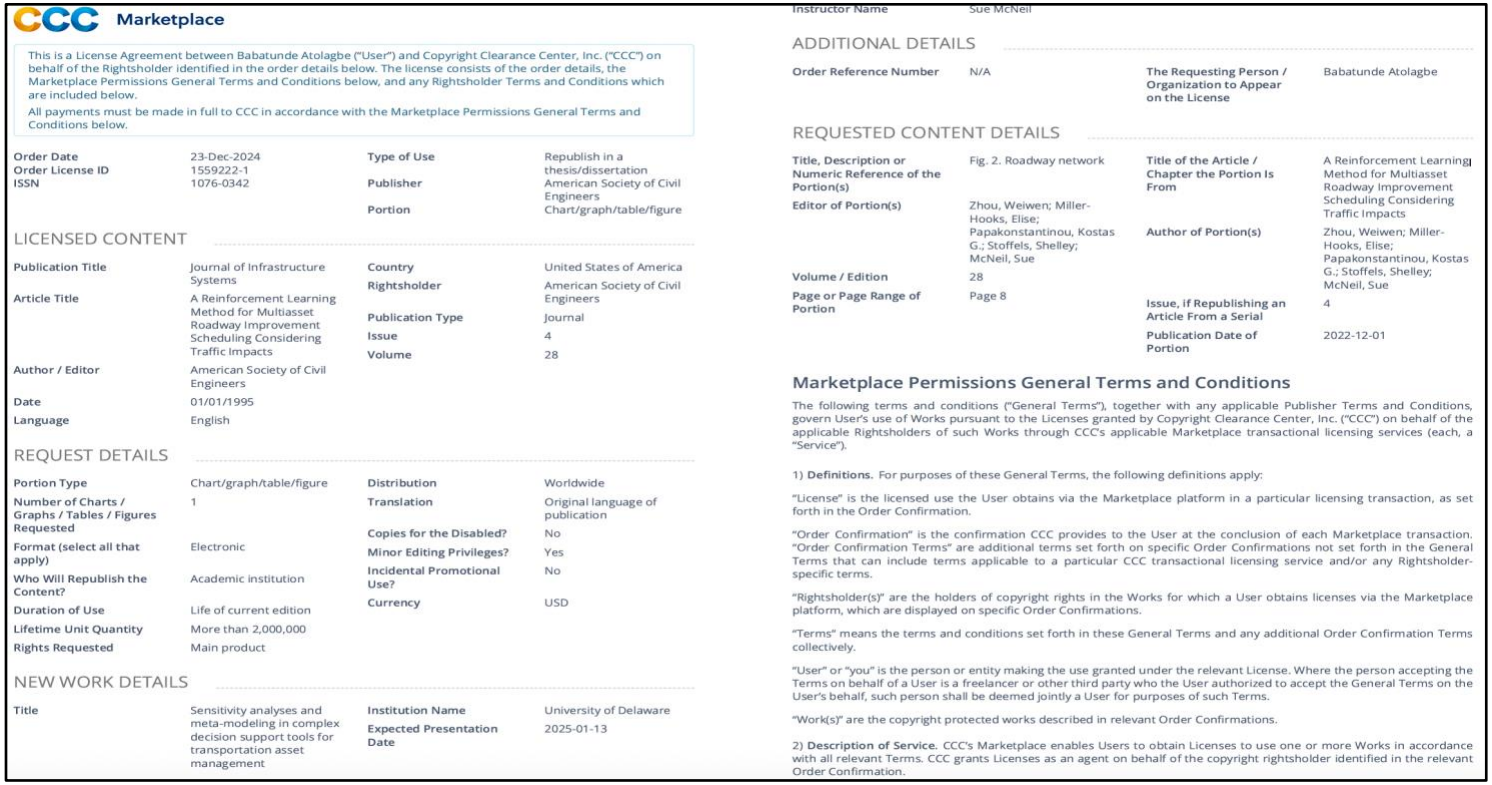

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		Expected Presentation Date	2025-01-13

Instructor Name: Sue McNeil

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1) **Definitions.** For purposes of these General Terms, the following definitions apply:

"License" is the licensed use the User obtains via the Marketplace platform in a particular licensing transaction, as set forth in the Order Confirmation.

"Order Confirmation" is the confirmation CCC provides to the User at the conclusion of each Marketplace transaction. "Order Confirmation Terms" are additional terms set forth on specific Order Confirmations not set forth in the General Terms that can include terms applicable to a particular CCC transactional licensing service and/or any Rightsholder-specific terms.

"Rightsholder(s)" are the holders of copyright rights in the Works for which a User obtains licenses via the Marketplace platform, which are displayed on specific Order Confirmations.

"Terms" means the terms and conditions set forth in these General Terms and any additional Order Confirmation Terms collectively.

"User" or "you" is the person or entity making the use granted under the relevant License. Where the person accepting the Terms on behalf of a User is a freelancer or other third party who the User authorized to accept the General Terms on the User's behalf, such person shall be deemed jointly a User for purposes of such Terms.

"Work(s)" are the copyright protected works described in relevant Order Confirmations.

2) **Description of Service.** CCC's Marketplace enables Users to obtain Licenses to use one or more Works in accordance with all relevant Terms. CCC grants Licenses as an agent on behalf of the copyright rightsholder identified in the relevant Order Confirmation.

3) **Applicability of Terms.** The Terms govern User's use of Works in connection with the relevant License. In the event of any conflict between General Terms and Order Confirmation Terms, the latter shall govern. User acknowledges that Rightsholders have complete discretion whether to grant any permission, and whether to place any limitations on any grant, and that CCC has no right to supersede or to modify any such discretionary act by a Rightsholder.

4) **Representations; Acceptance.** By using the Service, User represents and warrants that User has been duly authorized by the User to accept, and hereby does accept, all Terms.

Figure D-2: License granted for the use of image reproduced as Figure 5.1 of the dissertation