MOUNTAIN-PLAINS CONSORTIUM

MPC 24-531 | M. Abdallah, M. Ozbek and M. Ghafoori

OPTIMAL SELECTION OF UPGRADE AND MAINTENANCE INTERVENTIONS TO MINIMIZE LIFE-CYCLE COST

A University Transportation Center sponsored by the U.S. Department of Transportation serving the Mountain-Plains Region. Consortium members:

Colorado State University
North Dakota State University
South Dakota State University
University of Colorado Denver
University of Denver
University of Utah
Utah State University
University of Wyoming

Technical Report Documentation Page

1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.
MPC-676		

4. Title and Subtitle	5. Report Date
Optimal Selection of Upgrade and Maintenance Interventions to Minimize Life-Cycle Cost	August 2024
	6. Performing Organization Code
7. Author(s)	8. Performing Organization Report No.
Moatassem Abdallah Mehmet E. Ozbek Mahdi Ghafoori	MPC 24-531
9. Performing Organization Name and Address	10. Work Unit No. (TRAIS)
University of Colorado Denver Department of Civil Engineering Denver, CO, 80204 Colorado State University Department of Construction Management Fort Collins, CO 80523-1584	11. Contract or Grant No.
12. Sponsoring Agency Name and Address	13. Type of Report and Period Covered
Mountain-Plains Consortium North Dakota State University PO Box 6050, Fargo, ND 58108	Final Report
	14. Sponsoring Agency Code

15. Supplementary Notes

Supported by a grant from the US DOT, University Transportation Centers Program

16. Abstract

The maintenance and upgrade of infrastructure and buildings are critical for ensuring their performance, safety, and minimizing costs. However, inadequate planning and budget allocation, as well as resource constraints, often result in delayed maintenance, leading to costly interventions. To address these challenges, this study presents two novel models for optimizing the selection of upgrade and maintenance interventions to minimize the life-cycle cost while complying with annual budgets and performance requirements. The first model focuses on bridges and utilizes machine learning (ML) techniques to predict the condition of concrete bridge elements based on the National Bridge Inventory (NBI) and National Bridge Elements (NBE) databases. The model uses binary linear programming to identify the optimal selection of maintenance interventions and their timing to maximize bridge performance. The model's primary contributions are the development of a novel system that integrates ML techniques and linear programming, predicting bridge element conditions based on NBE's health index metric, and generating long-term maintenance plans to maximize the performance of bridges within available budgets. The second model focuses on buildings and proposes a computationally efficient model for identifying optimal upgrade and maintenance interventions to minimize the equivalent annual operation and maintenance cost (EAOMC) while complying with specified annual budgets and building operational performance. The model integrates reactive, preventive, and predictive maintenance strategies based on component types and incorporates simulation-based approach to evaluate energy and water consumption of buildings. The model's primary contributions are the development of a new model for identifying optimal selection of building upgrade and maintenance interventions, integrating maintenance and upgrade interventions to maximize economic benefits, and reducing operational and maintenance costs. Both models are evaluated using case studies and demonstrating new capabilities in identifying optimal upgrade and maintenance interventions for various operational budgets while achieving significant reductions in EAOMC and maximizing the performance of infrastructure and buildings. These models can assist decision-makers, such as highway agencies, in allocating limited financial resources for maintenance more efficiently and cost-effectively. The proposed approach can lead to significant economic and environmental benefits by reducing the life-cycle cost of infrastructure and buildings while ensuring their performance, safety, and sustainability.

17. Key Word	18. Distribution Statement
bridges, costs, innovation, life cycle costing, maintenance, mathematical models, modernization, optimization	Public distribution

19. Security Classif. (of this report)	20. Security Classif. (of this page)	21. No. of Pages	22. Price
Unclassified	Unclassified	55	n/a

Form DOT F 1700.7 (8-72) Reproduction of completed page authorized

Optimal Selection of Upgrade and Maintenance Interventions to Minimize Life-Cycle Cost

Moatassem Abdallah
Associate Professor
University of Colorado Denver
Department of Civil Engineering
Denver, Colorado, 80204
Moatassem.Abdallah@ucdenver.edu

Mehmet E. Ozbek
Professor and Joseph Phelps Endowed Chair
Colorado State University
Department of Construction Management
Fort Collins, Colorado, 80523-1584
Mehmet.Ozbek@colostate.edu

Mahdi Ghafoori
Research Assistant
University of Colorado Denver
Department of Civil Engineering
Denver, Colorado, 80204
Mahdi.Ghafoori@ucdenver.edu

August 2024

Acknowledgement

The authors would like to express their gratitude to the Mountain Plains Consortium, the U.S. Department of Transportation, the Research and Innovative Technology Administration, as well as the University of Colorado Denver and Colorado State University for providing the necessary funding for this research.

Disclaimer

The contents of this report reflect the views of the authors, who are responsible for the facts and the accuracy of the information presented herein. This document is disseminated in the interest of information exchange. The report is funded, partially or entirely, by a grant from the U.S. Department of Transportation's University Transportation Centers Program. However, the U.S. Government assumes no liability for the contents or use thereof.

ABSTRACT

The maintenance and upgrade of infrastructure and buildings are critical for ensuring their performance, safety, and minimizing costs. However, inadequate planning and budget allocation, as well as resource constraints, often result in delayed maintenance, leading to costly interventions. To address these challenges, this study presents two novel models for optimizing the selection of upgrade and maintenance interventions to minimize the life-cycle cost while complying with annual budgets and performance requirements. The first model focuses on bridges and utilizes machine learning (ML) techniques to predict the condition of concrete bridge elements based on the National Bridge Inventory (NBI) and National Bridge Elements (NBE) databases. The model uses binary linear programming to identify the optimal selection of maintenance interventions and their timing to maximize bridge performance. The model's primary contributions are the development of a novel system that integrates ML techniques and linear programming, predicting bridge element conditions based on NBE's health index metric, and generating long-term maintenance plans to maximize the performance of bridges within available budgets. The second model focuses on buildings and proposes a computationally efficient model for identifying optimal upgrade and maintenance interventions to minimize the equivalent annual operation and maintenance cost (EAOMC) while complying with specified annual budgets and building operational performance. The model integrates reactive, preventive, and predictive maintenance strategies based on component types and incorporates simulation-based approach to evaluate energy and water consumption of buildings. The model's primary contributions are the development of a new model for identifying optimal selection of building upgrade and maintenance interventions, integrating maintenance and upgrade interventions to maximize economic benefits, and reducing operational and maintenance costs. Both models are evaluated using case studies and demonstrating new capabilities in identifying optimal upgrade and maintenance interventions for various operational budgets while achieving significant reductions in EAOMC and maximizing the performance of infrastructure and buildings. These models can assist decision-makers, such as highway agencies, in allocating limited financial resources for maintenance more efficiently and cost-effectively. The proposed approach can lead to significant economic and environmental benefits by reducing the life-cycle cost of infrastructure and buildings while ensuring their performance, safety, and sustainability.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

1. INTRODUCTION AND OBJECTIVES

1.1 Introduction

Effective planning for bridge maintenance is crucial to ensure their performance, safety, and life-cycle costs. Timely and cost-effective interventions can prevent deterioration, enhance bridge performance, and avoid costly repairs. Inadequate planning and resource constraints often lead to delays in bridge maintenance, presenting challenges for decision-makers, particularly highway agencies, in allocating limited funds efficiently. Traditional stochastic methods for assessing bridge conditions, such as state-based and time-based approaches, have limitations. Data-driven methods, such as ML techniques, offer an opportunity to overcome these limitations and predict bridge element deterioration using historical condition data from databases like the National Bridge Inventory (NBI) and National Bridge Elements (NBE). Data-driven methods can provide more accurate predictions by analyzing large datasets and identifying patterns and relationships that may not be apparent to human experts. Additionally, these methods are flexible, adaptable to changing data, and eliminate subjective expert judgments. Leveraging historic condition data, data-driven approaches can be used to develop models capable of predicting bridge element deterioration and optimizing maintenance interventions while adhering to annual budgets.

Similarly, operation and maintenance costs of buildings are recognized as the most significant phase in a building's life cycle, surpassing the initial design and construction expenses. However, challenges such as design errors, lack of maintenance plans, and insufficient facility management knowledge often contribute to inflated building operational costs. Energy and water consumption further contribute to the high operation and maintenance costs of buildings. Despite regular maintenance practices, energy and water-saving investments are often overlooked due to various obstacles, including capital limitations, uncertainty regarding expected savings and payback periods, and a lack of skilled workers. Nonetheless, technological advancements in building systems provide a valuable opportunity to reduce operational costs. For example, upgrading fixtures, equipment, and envelope components can result in substantial energy and water consumption savings. To address the complexity of building systems and the limited availability of operational budgets, there is a need for innovative models that can assist decision-makers in identifying optimal upgrade and maintenance interventions for existing buildings.

This study aims to address the challenges faced in building operation and maintenance costs as well as bridge maintenance through innovative data-driven approaches. By integrating machine learning techniques and simulation-based evaluations, the proposed models offer decision-makers the ability to identify optimal upgrade and maintenance interventions for existing buildings and bridges. These models consider various factors such as energy and water efficiency, operational budgets, and performance requirements. The primary objectives are to minimize life-cycle costs, maximize performance, and enhance resource allocation efficiency for both buildings and bridges. The outcomes of this research will contribute to the body of knowledge by providing practical tools to support decision-making processes and promote sustainable and cost-effective maintenance practices for infrastructure and buildings.

1.2 Objectives

The objective of this research work is to develop an innovation optimization model that can identify optimal selection of upgrade and maintenance interventions to minimize life-cycle cost or equivalent annual cost of buildings and bridges. The model will be designed to maximize economic benefits by identifying an optimal schedule of interventions with respect to available annual budgets and service life to reduce operational and maintenance costs. This model is expected to provide much needed support to asset management teams in state DOTs to identify an optimal schedule of upgrades and maintenance interventions.

To this end, the sub-objectives of this research work are designed to: (1) identify upgrade and maintenance interventions for state DOT buildings and bridges; (2) achieve significant savings in the life-cycle cost of bridges and buildings by developing a new model that can identify optimal selection of upgrade and maintenance interventions; (3) document life-cycle cost savings of the model using case studies of a state DOT building and a bridge.

2. LITERATURE REVIEW

The existing research in the field of bridge and building maintenance can be broadly categorized into five areas: (1) bridge condition rating systems and deterioration models, (2) bridge maintenance prioritization methods, (3) bridge maintenance optimization models, (4) building energy and water efficiency measures, and (5) building upgrade and maintenance models and tools. This literature review will provide a detailed analysis of each of these categories.

2.1 Bridge Condition Rating Systems and Deterioration Models

Evaluating the condition of bridge elements is a vital step in estimating their remaining service lives and planning and prioritizing maintenance interventions. To this end, the Federal Highway Administration (FHWA) maintains the National Bridge Inventory (NBI), which was compiled in 1968 to include information on the following: (1) bridge identification, such as ID and location; (2) bridge types and specifications, such as design and geometric data; (3) operational data, such as average daily traffic and inventory rating; and (4) condition rating of primary components, including deck, superstructure, and substructure (FHWA 2023). The condition ratings in NBI are based on periodic visual inspections and are used to plan maintenance interventions for the bridge inventory. The NBI categorizes the condition of primary bridge components using discrete values ranging from 1 to 9, representing failed condition to excellent condition, respectively (FHWA 1995). In 2014, the National Bridge Elements (NBE) database was introduced as a mandatory tool for bridge asset management to increase accuracy of evaluating severity and extent of bridge condition deficiencies at the element level. The NBE includes data on bridge elements, their quantity, and percentage of each element in terms of good, fair, poor, and severe condition states. The NBE database uses a health index (HI) as the condition rating for each bridge element. The HI ranges from 0 to 100 and is calculated based on the percentages of element quantity in good, fair, poor, and severe condition states. This allows the NBE to consider the condition of each bridge element in a more detailed and comprehensive manner (FHWA 2014).

The aforementioned conditions are used to estimate the remaining service life of components, and to plan maintenance interventions to maintain the performance of bridges at acceptable levels to ensure their functionality. Several studies applied data-driven methods to predict the condition rating of primary bridge components based on NBI 9-class condition ratings (Alonso Medina et al. 2022; Bektas 2017; Chyad and Abudayyeh 2020; Fiorillo and Nassif 2019, 2020; Fraher et al. 2010; Hasan and Elwakil 2020; Liu and El-Gohary 2020; Lu et al. 2019; Miner and Alipour 2022; Nguyen and Dinh 2019). For example, Ariza et al. (2020) compared the performance of Markov, semi-Markov, and hidden Markov models and artificial neural networks methods in predicting the deterioration of concrete bridge decks. They applied the aforementioned methods on the same dataset and used mean square error (MSE) and mean average error (MAE) metrics to objectively compare the performance of each model. The results of their study showed that the artificial neural network (ANN) outperformed other methods with MSE and MAE of 0.21 and 0.32, respectively. Alogdianakis et al. (2021) presented an ANN model based on NBI to predict the deterioration of bridge conditions. In this study, the overall bridge conditions are classified in three groups, including good, fair, and poor. The overall bridge condition is classified as "good" if the minimum rating of primary components is at least 7, "fair" if the minimum rating of primary components is 5 or 6, and "poor" if the minimum rating is below 5. Moreover, this study applied a genetic algorithm to identify the best set of features for the ANN model to maximize its accuracy. Based on the case study performed on the overall accuracy of the Genetic Algorithm-Artificial Neural Network (GA-ANN) pattern recognition model was measured at 72.4%. Althaqafi and Chou (2022) developed several ANN classification models using the NBI dataset to identify the best ANN architecture for predicting the NBI 9-class condition rating of bridge decks, superstructures, and substructures. The best architecture achieved the MAE and R^2 score of 0.16 and 0.81 for deck, 0.17 and 0.81 for superstructure, and 0.21 and 0.76 for substructure, respectively. In a similar study, Liu and El-Gohary (2022) used a recurrent neural network classification model to predict the year-ahead NBI 9-class condition rating of primary bridge components, including decks, superstructures, and substructures, in the state of Washington. The developed model in this study achieved an average precision metric and recall metric values of 89.9% and 85.8%, respectively.

Despite the contribution of the aforementioned studies in predicting the deterioration of bridge condition, these studies primarily focused on the deterioration of major bridge components such as decks, superstructures, and substructures using NBI condition ratings; they did not examine the deterioration of specific elements at a granular level using metrics such as the NBE's HI elements. Additionally, these studies often relied on subjective expert opinions for choosing deterioration predictor features rather than using objective methods.

2.2 Bridge Maintenance Prioritization Methods

A number of studies presented budgeting methods for bridge maintenance prioritization to support decision-makers in planning and prioritizing maintenance and renovation activities (Amini et al. 2016; Contreras-Nieto et al. 2019; Das and Nakano 2021; Echaveguren and Dechent 2019; Fitriani et al. 2019; Gokasar et al. 2022; Hadjidemetriou et al. 2022; Huang et al. 2004; Kim et al. 2020; Valenzuela et al. 2010; Wakchaure and Jha 2011). For example, Zhang and Wang (2017) developed a bridge network model to prioritize maintenance interventions for a group of bridges while taking into account budget limitations. They introduced two performance indices: (1) static priority index (SPI), which assesses the performance of networks based on travel time between all possible origin-destination pairs within the network; and (2) dynamic priority index (DPI), which evaluates the performance of networks while considering the uncertainties affecting the performance of the transportation network. The case study's findings indicated that the DPI is a more effective ranking system compared with the SPI. Similarly, Contreras-Nieto et al. (2019) proposed a multi-criteria decision making model (MCDM) for prioritizing bridge maintenance tasks and budget allocation. They utilized analytic hierarchy process (AHP) to rank the maintenance activities based on bridge experts' perceptions of the relative importance of maintenance interventions on the deck, substructure, superstructure, and score in terms of bridge resiliency, riding comfort, safety, and serviceability. The results of the case study indicated that bridge decks are the most critical component when considering safety, serviceability, and comfort, and that the substructure is of highest importance when considering the resiliency criterion. Das et al. (2021) proposed a method for prioritizing bridge maintenance interventions using the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). The approach was based on criteria such as bridge condition index, delay cost, and accessibility. The case study results indicated that the failure of higher priority bridges can result in higher social costs. Other research works considered maintenance and social costs as well as environmental impacts in order to prioritize bridge maintenance interventions. For example, Gokasar et al. (2022) developed a hybrid MCDM model to rank bridge maintenance projects based on various criteria such as cost effectiveness, physical condition, social impact for travelers, and CO_2 emissions. To do this, they combined fuzzy weighted aggregated sum product assessment and TOPSIS to prioritize bridge maintenance projects. The case study results demonstrated that the environmental impacts of bridge maintenance projects can significantly influence the ranking of maintenance alternatives.

Although the aforementioned studies have significant contributions in presenting models for maintenance prioritization, they tend to focus on short-term bridge maintenance and are not capable of generating long-term maintenance plans that optimize the performance of bridges within available budgets.

2.3 Bridge Maintenance Optimization Models

Several research studies focused on developing maintenance optimization models to identify optimal maintenance interventions for bridges to minimize life-cycle costs (Bukhsh et al. 2018; Jaafaru and Agbelie 2022; Liu and Frangopol 2005; Nili et al. 2020, 2021; Peng et al. 2022; Sabatino et al. 2015; Saydam and Frangopol 2015; Wang and Piao 2019; Xie et al. 2018). These studies showed that implementing preventive maintenance (PM) can decrease the need for major maintenance interventions, leading to reduced maintenance costs and environmental impacts. For example, Ghodoosi et al. (2018) introduced an optimization model to minimize the life-cycle cost of bridge structures. This model integrates various databases, including asset inventory, a list of maintenance actions, and a deterioration model based on reliability, as well as an intervention effect model. The optimization model utilizes genetic algorithms to determine the optimal intervention scenarios. The model was applied to a simply supported bridge superstructure in a case study, which demonstrated that implementing less costly minor repair actions resulted in 4.5 times greater cost savings compared with the conventional approach of only conducting major repairs. In a similar study, Abdelkader et al. (2021) proposed a multi-objective differential evolution optimization model that aims to minimize maintenance time, cost, and greenhouse gas emissions. To evaluate the effectiveness of different intervention plans, the authors used a discrete event simulation model to simulate the process of replacing a bridge deck and a neural network model to predict the time, cost, greenhouse gas emissions, and resource utilization of each plan. In a case study, the proposed model achieved up to 71.01%, 27.87%, and 39.29% reductions in time, cost, and greenhouse gas emissions, respectively, compared with traditional methods. Nili et al. (2021) developed a simulation-based optimization model for identifying optimal maintenance interventions in bridge repair projects that aim to minimize agency and user costs while considering workspace constraints and predecessor relationships. The model used a discrete event simulation to determine the optimal sequence of repair activities for each intervention. In their case study, the proposed model resulted in an 11% reduction in user costs and a 4% reduction in crew costs compared with traditional methods. Xie et al. (2018) developed a multi-objective optimization model using a genetic algorithm to maximize safety and minimize the life-cycle cost and environmental impact of existing bridges. The model is designed to determine the optimal timing for performing preventive maintenance interventions. In their case study, the proposed model achieved up to 25% reduction in life cycle environmental impacts compared with conventional methods.

Despite the contributions of previous research on identifying optimal maintenance interventions, the results of these studies are limited by solution quality (i.e., the optimality of the solutions provided) or computational efficiency (i.e., the computational time required to generate the solutions). Moreover, there are no reported studies that present data-driven models that are capable of identifying optimal selection of maintenance interventions and their timing to maximize the performance of bridges while complying with available annual budgets.

2.4 Building Energy and Water Efficiency Measures

Several research studies have analyzed the impact that cooling and heating system upgrades have on buildings' energy consumption. These studies evaluated energy and cost savings of installing energy efficient HVAC (Heating, Ventilation, and Air Conditioning) systems in buildings. For example, a research study used field data from a high-rise residential case study building to create a calibrated energy model using EnergyPlus in order to examine the impact of compartmentalization and in-suite ventilation with heat recovery on overall space heating energy and greenhouse gas emissions. The case study showed that applying these measures leads to 78% reduction in total space heating energy and 83% reduction in associated greenhouse gas (GHG) emissions (Carlsson et al. 2019). Using Bayesian network technique, another research study presented an approach to select the most energy efficient HVAC system. In this study, a database from the 2012 Commercial Building Energy Consumption Survey (CBECS) was used to identify the optimal selection of HVAC systems (Tian et al. 2019). Other research studies have analyzed and evaluated the impact of upgrading wall and roof insulation on buildings' energy consumption in different regions and climates (Evin and Ucar 2019; Fantucci and Serra 2019; Huang et al. 2020; Jie et al. 2018; Juanicó 2020; Qiu et al. 2018; Ran et al. 2017; Ran and Tang 2018). For example, a recent study presented an optimization model to determine the optimum economic wall insulation thickness in existing buildings with combined heat and power-based district heating systems. The study showed that the increase in insulation thickness can reduce the annual heat demand, annual energy losses, heat medium temperature, and energy quality coefficient of heat medium (Jie et al. 2019). A number of research studies analyzed and evaluated the impact of glazing and upgrading windows on buildings' energy consumption (Fazel et al. 2016; Goia 2016; Gugliermetti and Bisegna 2007; Litti et al. 2020; Tällberg et al. 2019; Xue et al. 2019; Ye et al. 2014). For example, a research study evaluated the impact of replacing existing windows with more energy efficient ones or applying solar films on building energy usage. The study revealed that a combination of solar films and double glazed windows can reduce the annual HVAC energy consumption by up to 20% (Somasundaram et al. 2020). In addition, a number of research studies analyzed the impact of water heater systems on building energy consumption. For example, Kumar et al. studied the life-cycle cost and GHG emissions for five different types of water heating systems, including electric instantaneous, electric storage, natural gas instantaneous, natural gas storage, and heat pump. This study stated that five systems had major differences in the upfront cost, running cost, life-cycle cost, and GHG emissions. The study revealed that natural gas instant water heaters had the least upfront cost, the least life-cycle cost, and the second least GHG emissions after heat pumps (Kumar and Mathew 2018). Similarly, using life-cycle assessment and life-cycle cost analysis methods, another study suggested that natural gas should be used instead of electricity for water heating when both energy sources are practical options (Arpke and Hutzler 2005). Furthermore, analysis of lighting systems and their impact on building energy consumption is a focus of several studies. For example, Byun et al. presented an intelligent household LED lighting system to control an LED light according to the user's state and the surroundings. This system autonomously adjusts the minimum light intensity value to enhance energy efficiency and user satisfaction, which results in a power consumption reduction of up to 21.9% (Byun et al. 2013).

Water conservation measures are increasingly important due to climate change and a decrease in groundwater and surface water levels in the United States and many countries around the globe (AWWA 2019). Therefore, many research studies have focused on implementation and evaluation of water efficiency measures in existing buildings. For example, Arpke and Hutzler used life-cycle assessment and life-cycle cost analysis techniques to analyze the operational life cycle of plumbing fixtures and water-consuming appliances for an apartment, a college dormitory, a motel, and an office building for a 25-year period. The findings of this research revealed that the usage of higher-efficiency fixtures and appliances is environmentally and economically justifiable (Arpke and Hutzler 2005). Cahill et al. conducted a similar study to estimate the least-cost combination of long- and short-term conservation actions based on end-water-use parameter probability distributions generated from Monte Carlo sampling. The results of this study suggested that faucet and toilet retrofits have the highest potential for water savings (Cahill et al. 2013).

2.5 Building Upgrade and Maintenance Models and Tools

Several research studies assessed retrofit packages for large building stocks (Guardigli et al. 2018; Lim and Zhai 2017). For example, Zheng et al. proposed a bottom-up approach to analyze the relationship between building energy savings and the investments for different building types. The goal of this approach was to identify the energy-saving potential and to recommend effective energy efficiency measures. This paper studied the investments and energy savings for 100 buildings. This study's results showed that there was a strong correlation between investment and energy savings in renewable energy, lighting, and elevator systems retrofit. Moreover, there was a relatively weak correlation between investment and energy savings in air conditioning and envelope retrofit (Zheng et al. 2019a). In another study, Streicher et al. presented three economic assessment approaches for a national building stock to compare different deep energy retrofit packages. These three approaches assess the cost-effectiveness of large-scale retrofit packages from three different perspectives: (1) profit, which focuses on investment costs and the energy savings; (2) improvement, which implements the retrofits only at end of a lifetime of components; and (3) depreciation, which considers both environmental/energy and economic aspects. The results of the case study in this paper show 55% to 86% potential for a reduction in energy usage and 50% to 80% potential for a reduction in GHG emissions (Streicher et al. 2020). Although the aforementioned studies had significant contributions in identifying optimal selection of upgrade packages for large building stocks, they are not cable of the following: (1) providing building specific upgrade recommendations based on the specific building performance requirements, and (2) identifying upgrade packages based on owner specified constraints such as available upgrade budget.

Several research studies evaluated the economic feasibility of building upgrade measures on a building-level analysis (Amini Toosi et al. 2020; Gustafsson et al. 2019; Mangan and Oral 2015; Moschetti and Brattebø 2017; Pombo et al. 2016; Vilches et al. 2017). For example, Baldoni et al. presented a stochastic life-cycle cost methodology to evaluate the investments in energy efficiency retrofits economically. This study considered uncertainties associated with macroeconomic variables (e.g., inflation rate, market interest rate, price development rates) in determining expected returns and riskiness of these investments. The result of the exemplary case study in this paper showed that the macroeconomic variables and policies affect interest rates and therefore have an important role in economic evaluation of energy efficiency investments (Baldoni et al. 2019). Another study presented a framework to conduct an economic cost-benefit analysis for various energy efficiency upgrades using a static investment payback period and business rate of return. The study suggested that although energy efficiency upgrades lead to satisfactory energy conservation, the cost effectiveness of various upgrade measures in China cannot meet the profitability expectations due to the low energy price currently set in that country (Liu et al. 2018). Similarly, a research study presented a stepwise screening methodology for multiple building energy upgrade measures that considered economic and risk aspects. This study proposed building upgrade packages for stakeholders, calculated energy savings of various building measures, and quantified the associated risks of building upgrades. The proposed model was able to identify the upgrade package with the lowest risk and economic feasibility (Zheng et al. 2019b). A similar study presented a method to rank and select the most cost-effective upgrading measures. Based on life-cycle energy savings, life-cycle cost, and cost-effectiveness, this study ranked the selection of nine upgrading measures where lighting, air-conditioning, and refrigeration replacement were the top three cost effective measures, respectively; while wall retrofit, window replacement, and roof retrofit had the least cost effectiveness (Yuan et al. 2019). Although the aforementioned studies provided different life-cycle cost analysis methods that are capable of comparing/ranking different upgrade measures, they did not consider budget constraints, and therefore they are not capable of identifying the optimal selection of building upgrades based on owners' available budget. Moreover, these studies did not analyze a wide range of energy and water efficiency measures semiseriously to support decision-makers on their ongoing efforts to minimize utility costs.

Several optimization models and tools were developed for selecting building upgrade measures to reduce energy and water consumption (Evins 2013; Harvey 2013; Mariano-Hernández et al. 2021; Sanhudo et al. 2018). The existing studies used various methods for optimizing the selection of upgrade measures that include direct search methods such as linear programming and non-linear programming, evolutionary algorithms such as genetic algorithms, and meta-heuristic algorithms such as harmony search and particle swarm optimization. Hashempour et al. performed a literature review on existing optimization models in selecting building upgrades to identify trends and future research opportunities in this area. The study analyzed 153 models and showed that 41% of the papers used genetic algorithms, 13% used linear programming, 11% used brute-force search, and 35% used other methods for identifying building upgrades (Hashempour et al. 2020). Moreover, there is a limited number of studies that applied binary linear programming to identify the optimal selection of upgrade measures. Despite the contribution of the reported studies in Hashempour et al. (2020) that used linear programming, they are incapable of (1) considering budget upgrade and building performance constraints, and (2) modeling a comprehensive set of building upgrade measures (i.e., building fixtures, equipment, envelope components, and renewable energy systems simultaneously). Note that standard measures, such as building equipment upgrades and deep upgrades such as building envelope components, should be considered together to achieve water and energy savings beyond 45% (PNNL 2011).

Although the aforementioned studies had significant contributions in identifying optimal selection of building upgrades, the generated results are constrained by solution quality and/or computational efforts. Specifically, there are limited or no reported studies that (1) used EAUUC to economically evaluate various building upgrade measures to maximize savings while complying with user-specified requirements for building operational performance and available upgrade budgets; (2) implemented binary linear optimization algorithms that result in global optimum solutions in short computational time; and (3) modeled a wide range of upgrade measures for building fixtures and equipment as well as envelope components supported by updateable databases of building products. The present research study is designed to address the aforementioned research gaps.

3. Data-Driven Bridge Maintenance System to Maximize Performance within Available Budgets

The objective of this chapter is to develop a data-driven system that is capable of predicting condition of concrete bridge elements to identify optimal selection of maintenance interventions and their timing to maximize performance of bridges within available budgets. The system consists of (1) machine learning (ML) models to predict the condition of concrete bridge elements, and (2) a bridge maintenance optimization model to identify optimal maintenance interventions and their timing, as shown in Figure 3.1.

The input data for the developed system is provided via a spreadsheet that includes information on: (1) bridge characteristics, including type, age, location, construction, and geometry; (2) operational data, such as average daily traffic and inventory rating; (3) bridge element data, including count and quantity of each element, as well as deterioration conditions based on the HI ratings; and (4) a study period, which represents the planning horizon for maintenance interventions, as shown in Figure 3.1.

The bridge element deterioration models perform multistep forecasting of the HI elements over the specified study period based on the bridge's unique specifications and ambient conditions, such as age, location, and average daily traffic. ML methods are used to predict the deterioration of bridge elements due to their capability of predicting non-stationary and nonlinear time series data. The bridge element deterioration forecasting models are developed in four main steps: (1) data preprocessing, where the NBI and NBE data are concatenated and prepared to be used for ML model development; (2) feature selection, where factors affecting the bridge elements' deterioration are identified; (3) model development, where four different ML models are trained and tested using selected features from the NBI data; and (4) predictive performance evaluation, where the predicted data from the test dataset is compared with reported values, as shown in Figure 3.1.

The maintenance intervention optimization model is designed to identify optimal selection of maintenance interventions and their timing to maximize bridge performance while complying with available annual budgets. The optimization model is developed in three main phases that focus on (1) identifying model decision variables, (2) formulating objective function and constraints, and (3) implementing model computations using binary linear programming, as shown in Figure 3.1. The present model is designed to evaluate the cost-effectiveness of maintenance interventions based on the performance level of bridge elements, as measured by their HI, and the associated maintenance costs over the specified study period. Note that the optimization model identifies the optimum maintenance interventions for bridge elements based on the predicted HI from the bridge element deterioration model, as shown in Figure 3.1. Binary linear programming is used to perform the optimization model computations due to its capability of identifying optimal solutions in a short computational time. A concrete bridge case study is analyzed to evaluate the performance of the system and demonstrate its capabilities. The present system can support decision-makers, such as highway agencies, in allocating limited financial resources for bridge maintenance more efficiently and cost-effectively.

The present system is designed to generate output data through charts and action reports. The output data include: (1) annual maintenance cost charts of recommended maintenance plans within the study period; (2) charts of the annual bridge HI and the annual HI of individual elements over the study period; and (3) action reports summarizing detailed recommendations for maintenance interventions within the specified study period and maintenance budget.

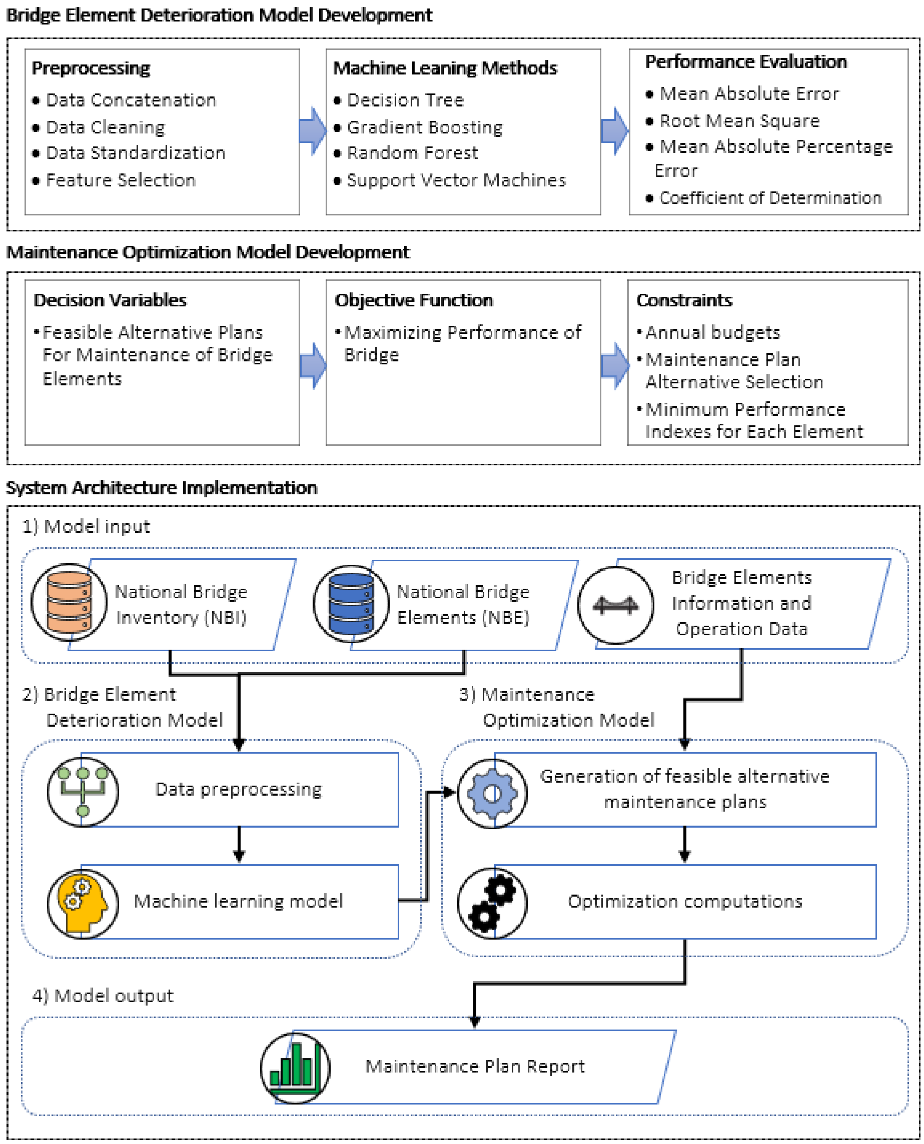

Figure 3.1 System architecture and development of components

3.1 Bridge Element Deterioration Model

3.1.1 Data Preprocessing

Data preprocessing is a crucial step in the development of ML models, as it ensures that data are suitable for further analysis and use in machine learning. This process is performed in three steps: (1) concatenation of the NBI and NBE data, in which the datasets are concatenated to form a comprehensive dataset; (2) data cleaning and redundancy elimination, in which redundant or duplicate information are removed; and (3) data standardization and transformation, in which numeric data are standardized using a standard scaler and categorical data are encoded using one-hot encoding.

3.1.2 Feature Selection

The NBI and NBE databases are used to objectively assess the factors that affect the deterioration of concrete bridge elements. To this end, an entropy-based mutual information (MI) method from information theory is employed. The MI method is a nonparametric entropy-based technique that can detect linear and non-linear dependencies between variables. The research team selected the K-nearest neighbors-based MI estimation method (KNN-based MI) over other MI estimation methods that use "binning" of data, as it can more accurately identify mutual information (Farahani et al. 2022; Franzen et al. 2020; Ross 2014). In this method, MI between variable X and Y can be calculated based on average I_i scores for all datapoints as shown in Equation (3-1) to Equation (3-3).

$$I(X,Y) = \frac{\sum_{i=1}^{N} I_i}{N} \tag{3-1}$$

$$I_i = \psi(N) - \psi\left(N_{x_i}\right) + \psi(K) - \psi(m_i) \tag{3-2}$$

$$\psi(t) = \ln(t) - \frac{1}{2t} \tag{3-3}$$

Where: $I(X,Y)$ is the MI between variable X and Y; N_{x_i} is number of data points whose value equals x_i in entire dataset; K is number of neighbors that is considered for the analysis; m_i is the number of neighbors within the distance to the Kth neighbor of data point i; $\psi(t)$ is digamma function that can be calculated as shown in Equation (3-3).

3.1.3 Machine Learning Methods

To predict the HI of various common bridge elements in the NBE database, four ML models are developed for each bridge element using the most influential predictor features identified in the feature selection step. A range of ML techniques with various hyperparameters are tested to develop these models, including: (1) decision trees (DT), (2) random forests (RF), (3) gradient boosting (GB), and (4) support vector machines (SVM). The specific parameters and architecture of these models are outlined in Table 3.1. The mathematical formulations of these algorithms are not discussed here as they can be found in ML resources (Courville Aaron Goodfellow Ian 2016). Note that all the models are developed using Adam optimizer with mean squared error loss functions for 200 epochs. The ML models are implemented using the Python programming language and the scikit-learn library.

Table 3.1 The parameters of the ML models and their respective values

ML Model	Parameters	Values
DT	Criterion function	Mean squared error
	Minimum samples to split an internal node	2
	Minimum samples for leaf nodes	1
RF	Number of estimators (Trees)	100
	Criterion function	Mean squared error
	Minimum samples to split an internal node	2
	Minimum samples for leaf nodes	1
SVM	Kernel	Radial basis function
	Tolerance for stopping criterion	0.001
	Epsilon	0.1
	Gamma	0.05
GB	Learning rate	0.1
	Number of estimators	100
	Maximum depth	3
	Loss function	Least squares regression
	Criterion function	Friedman mean squared error
	Minimum samples to split an internal node	2
	Minimum samples for leaf nodes	1

3.1.4 Predictive Performance Evaluation Metrics

Four commonly utilized metrics for evaluating the predictive performance of machine learning models, including mean absolute error (MAE), mean square error (MSE), mean absolute percentage error (MAPE), and coefficient of determination (R^2 score), are employed to assess the performance of the developed models in this study. MAE measures the average absolute difference between the predicted and true values of the data points in the test dataset. This metric provides a general understanding of the model's performance by conveying the magnitude of the errors made by the model in its predictions. MSE measures the average of the squared differences between the predicted and true values, with larger errors having a greater impact on the MSE value. This metric is more sensitive to outliers than MAE and can provide information about the model's ability to predict data points with less frequency. MAPE calculates the average relative error of the data points in the test dataset as a percentage, which allows for comparison of error across different magnitude ranges of the true values. It can provide insight into the model's overall accuracy with respect to the magnitude of the true values. R^2 score, also known as the coefficient of determination, indicates the ability of the model to predict future samples. It is a measure of how well the model fits the data, with a score of 1 indicating a perfect fit and a score of 0 indicating a poor fit. A high R^2 score suggests that the model is able to make accurate predictions using the information it has learned from the training data. MAE, MAPE, RSME, and R^2 score can be calculated based on predicted and true values of datapoints, as shown in Equation (3-4) to Equation (3-7), respectively.

$$\mathrm{MAE}(y, \hat{y}) = \frac{1}{N_t} \sum_{i=1}^{N_t} |y_i - \hat{y}_i| \tag{3-4}$$

$$\mathrm{SME}(y, \hat{y}) = \sum_{i=1}^{N_t} \frac{(y_i - \hat{y}_i)^2}{N_t} \tag{3-5}$$

$$MAPE(y, \hat{y}) = \frac{1}{N_t} - \sum_{i=1}^{N_t} \frac{|y_i - \hat{y}_i|}{y_i} \tag{3-6}$$

$$R^2(y, \hat{y}) = 1 - \frac{\sum_{i=1}^{N_t}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N_t}(y_i - \bar{y})^2} \tag{3-7}$$

Where: $\hat{y}$ represents the predicted value of datapoint i, y_i represents the true value of datapoint i, N_t is total number of samples in the test dataset, and $\bar{y}$ is average value of y_i.

3.2 Optimization Model Development

3.2.1 Decision Variables

The decision variables are designed to represent all feasible interventions for maintenance of bridge elements for a predefined period of study. These variables cover all the feasible maintenance interventions for bridge elements, including reinforced concrete deck, reinforced concrete top flange, prestressed concrete closed web/box girder, prestressed concrete girder/beam, reinforced concrete column, reinforced concrete pier wall, reinforced concrete abutment, reinforced concrete pier cap, reinforced concrete culvert, strip seal joint, pourable joint, steel bridge rail, reinforced concrete bridge rail, wearing surfaces, and steel protective coating. These alternatives are modeled using "$X_{e,y,i}$" which is a binary decision variable to model the selection of maintenance intervention number "i" in the year "y" for element "e" from a set of feasible alternatives, as shown in Figure 3.2. The decision variable "$X_{e,y,i}$" is designed to range from the first alternative intervention "$X_{e,y,1}$" for the element "e", to alternative intervention "X_{e,y,NA_e}" representing the total number of feasible interventions "NA_e" for the element "e" in year "y", as shown in Figure 3.2. Note that these maintenance intervention alternatives are designed to represent a spectrum of improvement in conditions, ranging from zero improvement, no maintenance intervention, to maximum repair of an element at 100% with user-defined increments such as 5%. "y" is designed to range from $y = 1$, the first year in the study period, to $y = \mathrm{Y}$ representing the total number of years in the study period, as shown in Figure 3.2. "e" is designed to range from, $e = 1$ for reinforced concrete column to $e = 15$ for strip seal joints, as shown in Figure 3.2. For example, $X_{15,3,2} = 1$ represents the selection of the 2nd maintenance intervention for element type 15, strip seal joints, in the year 3.

	Reinforced Concrete Column ($e = 1$)				Strip Seal Joints ($e = 15$)		
Study Period ($\mathrm{Y} = 50$ years)	$\boldsymbol{X_{1,1,1}}$	...	$\boldsymbol{X_{1,1,NA_1}}$	...	$\boldsymbol{X_{15,1,1}}$	...	$\boldsymbol{X_{15,1,NA_{15}}}$
	....	...	...	...	....	...	...
	$\boldsymbol{X_{1,50,1}}$	...	$\boldsymbol{X_{1,50,NA_1}}$	...	$\boldsymbol{X_{15,50,1}}$	...	$\boldsymbol{X_{15,50,NA_{15}}}$

Figure 3.2 Decision variables

3.2.2 Objective Function

The objective function of the optimization model is designed to identify optimal selection of maintenance interventions and their timing to maximize performance of bridges while complying with available annual budgets. The bridge performance index over the study period can be calculated by weighted average of performance index of bridge elements, including reinforced concrete deck, reinforced concrete top flange, prestressed concrete closed web/box girder, prestressed concrete girder/beam, reinforced concrete column, reinforced concrete pier wall, reinforced concrete abutment, reinforced concrete pier cap, reinforced concrete culvert, strip seal joint, pourable joint, steel bridge rail, reinforced concrete bridge rail, wearing surfaces, and steel protective coating during the predefined study period, as shown in Equation (3-8). To calculate the weighted average performance index of bridge elements, the weight of each element can be determined through expert opinion. For example, these weights can be determined based on the cost of each element reconstruction and replacement. The performance of each bridge element is measured based on NBE's HI. Accordingly, the condition of bridge elements for each year can be calculated based on the ML predictions, time of maintenance interventions, and improvement in conditions due to implementation of maintenance interventions, as shown in Equation (3-9).

$$Maximize: ABPI = \frac{\sum_{\mathrm{e}=1}^{15} \sum_{y=1}^{Y} EHI_{e,y} \times W_e}{\sum_{\mathrm{e}=1}^{15} \sum_{y=1}^{Y} W_e} \tag{3-8}$$

Where: "$ABPI$" is average of bridge performance indexes over the study period; "$EHI_{e,y}$" is HI of element "e" in year "y" which can be calculated based on improvement in conditions due to maintenance interventions and predicted HI of elements, as shown in Equation (3-9); and "W_e" is user specified importance weight for element "e".

$$EHI_{e,y} = PHI_{e,y} + \sum_{\mathrm{t}=1}^{y} \sum_{\mathrm{i}=1}^{NA_e} X_{e,\mathrm{y},i} \times ME_{e,\mathrm{y},i} \tag{3-9}$$

Where: $PHI_{e,y}$ is predicted HI of element "e" in year "y" which is estimated using ML models; and $ME_{e,\mathrm{y},i}$ is improvement in condition of element "e" due to maintenance intervention "i" in year "y".

3.2.3 Optimization Constraints

To ensure the practicality and feasibility of the generated solutions, three types of constraints are integrated in the model: (1) annual maintenance budget, (2) maintenance intervention selection, and (3) minimum acceptable performance of bridge elements. The annual budget constraints are integrated in the model to ensure that the costs of bridge maintenance interventions do not exceed the available budget for each year. The available budget for each year is specified by the user, as shown in Equation (3-10). Note that savings from year (y) are added to year (y + 1) as savings from previous years can be used for maintenance of bridge elements in future years, as shown in Equation (3-10). The element's maintenance cost is estimated in the model based on improvement in element conditions due to implementing maintenance interventions, measured by NBE's HI, and bridge element replacement costs, as shown in Equation (3-11). The cost of replacing bridge elements includes costs for demolishing existing elements (if needed), materials, and labor and is calculated based on the quantity of each element and cost references such as RSMeans (RSMeans 2020).

$$\sum_{e=1}^{15}\sum_{y=1}^{t}\sum_{i=1}^{NA_e} X_{e,y,i} \times MC_{e,y,i} < y \times AB \qquad \forall\, t = 1, \dots, Y \tag{3-10}$$

Where: "$MC_{e,y,i}$" is the cost of maintenance intervention number "i" in year "y" for element "e" which can be calculated based on construction cost of elements and improvement in their conditions due to maintenance interventions, as shown in Equation (3-11); and AB is the user-specified annual budget.

$$MC_{e,y,i} = ECC_e \times \left(\frac{ME_{e,y,i}}{100 - THI_e}\right) \tag{3-11}$$

Where: ECC_e is the construction cost of element "e", and THI_e is terminal HI, which represents the minimum acceptable condition for element "e".

The maintenance intervention selection constraints are integrated in the model due to utilization of linear programming to restrict the optimization model to select a single maintenance intervention from the set of alternatives for each element in each year, as shown in Equation (3-12). Additionally, the minimum performance constraints are designed to guarantee that maintenance interventions are carried out on bridge elements prior to their performance index falling below their terminal HI, as shown in Equation (3-13).

$$\sum_{i=1}^{NA_e} X_{e,y,i} = 1 \qquad \forall\, e = 1, \dots, 15 \quad \forall\, y = 1, \dots, Y \tag{3-12}$$

$$EHI_{e,y} \geq THI_e \qquad \forall\, e = 1, \dots, 15 \quad \forall\, y = 1, \dots, Y \tag{3-13}$$

3.2.4 Optimization Computations

The computations of the present model are performed using binary linear programming due to its capability of identifying global optimum solutions in a short computational time. The model is coded in MATLAB 2022b and executed using the MILP solver of Gurobi.

4. Optimization Model for Planning Upgrade and Maintenance Interventions for Buildings

The objective of this paper is to develop a new model for identifying the selection of upgrade and maintenance interventions and their timing for existing buildings to (1) minimize equivalent annual operation and maintenance cost (EAOMC); and (2) comply with specified annual budgets, building operational performance, and predefined study period. To this end, the model is designed to incorporate reactive, preventive, and predictive maintenance strategies to optimize facility maintenance and equipment operability and minimize building EAOMC. A reactive strategy is applied for any unexpected maintenance issues that might arise during building operations such as a broken window. A preventive strategy is used for less critical components such as light bulbs. These components are replaced, regardless of their condition, before or at the end of their service life as reported by manufacturers. Predictive maintenance strategy is used for more costly and critical components under the effect of continuous degradation action, such as HVAC systems. The Weibull probability method is used to estimate the service lives of components with predictive maintenance strategy. Furthermore, the model considers upgrade interventions for each building component to identify its optimal upgrade plan and its timing to minimize EAOMC. Integrating maintenance and upgrade interventions can provide significant opportunities to optimize the use of available annual budgets for gradual upgrade of buildings. Despite the conventional maintenance methods that solely focus on repair and replacement interventions, the present model is designed to integrate building repair, replacement, and upgrade interventions to maximize economic benefits from building operation by reducing operational and maintenance costs.

The present problem can be solved using different approaches: (1) a probabilistic approach where the model uses probabilities to model future conditions of building equipment and potential building upgrades; or (2) a deterministic approach where the model uses building maintenance strategies, energy simulation, and available building products in the market to generate an initial plan for maintaining and upgrading the building for a specified study period. The authors chose the second approach for the following reasons: (1) the probabilistic approach will add significant complexity to the present model and its search space; (2) the deterministic approach can generate specific action reports to maintain and upgrade buildings; (3) the results of the deterministic approach can be updated iteratively (e.g., each year) as actual conditions of the building are collected and new building products become available in the market; and (4) accidental failure and unplanned maintenance issues are considered in the deterministic approach by allocating a separate budget to cover unforeseen maintenance issues.

The present model is expected to provide much needed support to building owners and operators in identifying an optimal schedule of upgrade and maintenance interventions based on the latest products in the market and available annual budgets. The optimization model is developed in three main phases that focus on the following: (1) identifying model decision variables, formulating objective function and constraints; (2) implementing model computations using binary linear programming; and (3) analyzing the performance of the optimization model using an existing building. The following sections provide details of each of these three development phases.

4.1 Formulation Phase

4.1.1 Decision Variables

The decision variables are designed to model all feasible alternative plans for repairing, replacing, or upgrading (RRU) building components that affect building energy and water consumption for a predefined period of study. These alternatives cover all the feasible RRU plans for building components, including light bulbs, fixtures, and motion sensors; hand dryers; vending machines; water faucets; urinals;

toilets; water heaters; photovoltaic (PV) systems; elevators; cooling and heating equipment; window glazing and films; wall insulation; and roof insulation.

The model is designed to integrate three types of decision variables: (1) $P_{t,l,p}$ is a binary decision variable to model the selection of RRU plan number p for component type t in building location l from a set of feasible alternatives; (2) CS_p is a binary decision variable to model the selection of RRU plan number p for a combination of cooling system, heating system, wall insulation, roof insulation, and window glazing and films from a set of feasible alternatives; and (3) Q_p is a binary decision variable to model the selection of upgrade plan number p for a PV system. Decision variable $P_{t,l,p}$ is designed to range from the first alternative plan $P_{t,l,1}$ for components of type t, in space l, to alternative plan $P_{t,l,N_{t,l}}$, representing the total number of feasible plans $N_{t,l}$. t is designed to range from, $t = 1$ for light fixtures to $t = 14$ for window glazing and films. Similarly, l is designed to range from the first space, $l = 1$, that contains the fixture or equipment of type t to $l = NS_t$ which represents the total number of spaces that contain the component type t. For example, $P_{1,2,3} = 1$ represents the selection of the third RRU plan for component type 1, lighting fixtures, at space #2 of the building. Decision variable CS_p is designed to range from the first RRU plan, CS_1, for the combination of the above heating and cooling system and envelope components to plan CS_{N_c} which is the maximum number of feasible alternative RRU plans. For example, CS_4=1 represents the selection of the fourth RRU plan for the combination of the aforementioned components. Decision variable Q_p is designed to range from the first upgrade plan, Q_1, for PV systems to plan Q_{N_p} representing the total number of feasible upgrade plans N_p. For example, $Q_3 = 1$ represents the selection of the third PV system upgrade plan to offset the energy demand of the building.

In order to linearize the problem based on feasible alternative products and the remaining service lives of building components, the model generates all feasible RRU plans for each component in the building. Each RRU plan specifies each upgrade and maintenance intervention that should take place in each year. In this regard, generated alternative plans for the decision variable $P_{t,l,p}$ are designed as vectors with the length of study period Y that include the RRU intervention for each year. Note that each value in the vector corresponds to the intervention plan in year "y" and can be 0, -1, 1, or greater than 1 that represent, respectively, no interventions, repairing existing component, replacing component with the same product, and upgrading component with an alternative that corresponds to the value in the vector. For example, $P_{1,1,1}(1) = 2$, $P_{1,1,1}(2) = 0$, and $P_{1,1,1}(6) = 1$ represent upgrading component with product ID #2 in year 1, no interventions in year 2, and replacing component with the same product in year 6, for light bulbs ($t = 1$), in building location #1 ($l = 1$), and for alternative plan 1 ($p = 1$). Similarly, alternative plan CS_p is designed to represent the selection of a matrix that includes a combination of five vectors with the length of study period Y for cooling systems, heating systems, wall insulation, roof insulation, and window glazing and films in each year, respectively. For example, $CS_1(1,1)$= -1, $CS_1(1,2) = 1, CS_1(1,3) = 2, CS_1(1,4) = 0,\ and\ CS_1(1,5) = 0$ represent repairing cooling system, replacing heating system with the same product, upgrading window glazing with product ID #2, no intervention for wall, and no intervention for roof in year 1, respectively. Finally, alternative plan Q_p is designed to represent a vector with the length of study period Y that includes upgrading PV systems for each year. $Q_p\ (y)$ is designed to range from zero, no installation of PV system, to installation of maximum capacity of PV systems with user-defined increments such as 1kW in year "y". For example, $Q_2\ (2) = 1$ represents installing PV system with system capacity, such as 1kW, in year 2 to offset building energy demand.

4.1.2 Objective Function

The objective function of the optimization model is designed to minimize the EAOMC of existing buildings. Different upgrade and maintenance interventions for building components result in unequal service lives. Therefore, the equivalent annual cost method is used to analyze the cost of different upgrade and maintenance plans because it can compare different RRU plans with different service lives. The EAOMC can be calculated by adding up the EAOMC of all building components, as shown in Equation (4-1). The EAOMC of each building component is calculated based on the net present value of RRU plan costs, operational costs, service life, and annuity factor, as shown in Equation (4-2) to Equation (4-8). Service lives of components with predictive maintenance strategy are calculated using the Weibull probability method. This method considers degradation as a function of time and estimates the service life of an RRU plan based on the component's initial condition, time of RRU interventions, and expected improvement in conditions, as shown in Equation (4-9) and Equation (4-10). The component's repair cost is estimated in the model based on (1) expected improvement in component conditions due to implementing maintenance activities, and (2) component replacement cost (Grussing and Marrano 2007), as shown in Equation (4-11). The upgrade or replacement costs of building components are designed to include demolishing existing components, purchasing new materials, and installing new building components. Moreover, annual operational costs include energy and water cost and annual routine maintenance cost such as replacing HVAC system filters. The annual energy consumption and cost of building components are calculated based on their technical specifications, operational schedule, and energy cost rate. Energy consumption and cost of cooling and heating systems are calculated using OpenStudio and based on building characteristics, cooling and heating system characteristics, operational schedule, envelope components, and energy cost rate. Similarly, energy consumption and cost of building water heaters are calculated using OpenStudio and based on building characteristics, water heater characteristics, operational schedule, and energy cost rate. Finally, building annual water consumption and cost are calculated using the LEED guidelines based on specifications of plumbing fixtures, type of building, number of full-time occupants and visitors, and water cost rate (USGBC 2018). Note that the performance of each building component in terms of energy and water consumption over its service life is assumed uniform to simplify the model computations.

$$EAOMC = \sum_{t=1}^{8}\sum_{l=1}^{NS_t}\sum_{p=1}^{N_{t,l}} P_{t,l,p} \times EACP_{t,l,p} + \sum_{p=1}^{N_c} CS_p \times EACCS_p + \sum_{p=1}^{N_p} Q_p \times EACPV_p \tag{4-1}$$

Where: $EAOMC$ is the building equivalent annual operation and maintenance cost; $EACP_{t,l,p}$ is the equivalent annual cost of RRU plan p for component type t in building location l which is calculated based on RRU costs, service lives, and annual operational cost, as shown in Equation (4-2); $EACCS_p$ is the equivalent annual cost of RRU plan p for the combination of cooling system, heating system, wall insulation, roof insulation, and window glazing and films, and is calculated using RRU costs, service lives of components, and annual operational cost, as shown in Equation (4-3); and $EACPV_p$ is the equivalent annual cost of upgrade plan p for implementing PV system at the building site, and is calculated based on upgrade costs, service lives, and annual operational savings, as shown in Equation (4-6).

$$EACP_{t,l,p} = \begin{cases} \dfrac{\sum_{y=1}^{PSL_{t,l,p}} NPV\left(RRUC_{t,l,p}(y) + OC_{t,l,p}(y), r, y\right)}{A\left(PSL_{t,l,p}, r\right)}, & t < 4 \ \ (preventive\ plans) \\ \dfrac{\sum_{y=1}^{ESL_{t,l,p}} NPV\left(RRUC_{t,l,p}(y) + OC_{t,l,p}(y), r, y\right)}{A\left(ESL_{t,l,p}, r\right)}, & t \geq 4 \ \ (predictive\ plans) \end{cases} \tag{4-2}$$

Where: NPV is net present value that is calculated based on a specified discount/interest rate, and number of years, as shown in Equation (4-7); A is annuity factor which is calculated based on an annual interest rate, r, and service life of an alternative, as shown in Equation (4-8); $PSL_{t,l,p}$ is predetermined service life of RRU plan $P_{t,l,p}$ which is calculated based on manufacturer's recommendations; $ESL_{t,l,p}$ is the estimated service life of RRU plan $P_{t,l,p}$ which can be calculated based on components deterioration model, as shown in Equation (4-9); $RRUC_{t,l,p}(y)$ is repair, replacement, and upgrade cost of plan $P_{t,l,p}$ in year y; $OC_{t,l,p}(y)$ is operational cost in year y corresponding to RRU plan $P_{t,l,p}$.

$$EACCS_p = EARRU_p^C + EARRU_p^H + EARRU_p^W + EARRU_p^R + EARRU_p^G + EAOC_p \tag{4-3}$$

$$EARRU_p^X = \frac{\sum_{y=1}^{ESL_p^X} NPV\left(RRUC_p^X(y), r, y\right)}{A\left(ESL_p^X, r\right)}, X \in \{C, H, W, R, G\} \tag{4-4}$$

$$EAOC_p = \frac{\sum_{y=1}^{Min(ESL_p^C, ESL_p^H, ESL_p^W, ESL_p^R, ESL_p^G)} NPV\left(OCCS_p(y), r,\ y\right)}{A\left(Min(ESL_p^C, ESL_p^H, ESL_p^W, ESL_p^R, ESL_p^G), r\right)} \tag{4-5}$$

Where: $EARRU_p^C$, $EARRU_p^H$, $EARRU_p^W$, $EARRU_p^R$, $EARRU_p^G$ are equivalent annual RRU cost of cooling system, heating system, wall insulation, roof insulation, and window glazing and film corresponding to combination CS_p, respectively, and are calculated using RRU costs and service lives of components, as shown in Equation (4-4); $EAOC_p$ is equivalent annual operational cost corresponding to combination CS_p, and is calculated using operational costs in each year, as shown in Equation (4-5); $RRUC_p^X(y)$ is repair, replacement, and upgrade cost for component X in year y corresponding to combination CS_p; ESL_p^X is the estimated service life for component X corresponding to combination CS_p; $OCCS_p(y)$ is operational cost in year y corresponding to combination CS_p. $ESL_p^C, ESL_p^H, ESL_p^W, ESL_p^R, ESL_p^G$ are estimated service lives for cooling system, heating system, wall insulation, roof insulation, and window glazing and film corresponding to combination CS_p, respectively.

$$EACPV_p = \frac{\sum_{y=1}^{ESLQ_p} NPV\left(UCQ_p(y) + OCQ_p(y), r, y\right)}{A\left(ESLQ_p, r\right)} \tag{4-6}$$

$EAOC_p$ is equivalent annual operational cost corresponding to combination CS_p. $ESLQ_p$is estimated service life of PV system upgrade plan Q_p; $UCQ_p(y)$ is upgrade cost in year y corresponding to upgrade plan Q_p; $OCQ_p(y)$ is operational cost of PV systems in year y corresponding to upgrade plan Q_p.

$$NPV(FC, r, y) = \frac{\mathrm{FC}}{(1+r)^y} \tag{4-7}$$

$$A(SL, r) = \frac{1 - \frac{1}{(1+r)^{SL}}}{r} \tag{4-8}$$

Where: FC is the future cost at year number y, r is discount rate, and SL is service life of RRU plan.

$$ESL_{t,l,p} = y + \beta_{t,l} \times \left(\frac{\log\left(\frac{C_{t,l,p}(y)}{TC_{t,l}}\right)}{\log\left(\frac{100}{TC_{t,l}}\right)} \right)^{1/\alpha_{t,l}} \tag{4-9}$$

$$C_{t,l,p}(y) = IC_{t,l} \times \left(\frac{100}{TC_{t,l}}\right)^{-(\frac{y}{\beta_{t,l}})^{\alpha_{t,l}}} + ME_{t,l} \tag{4-10}$$

Where: $\beta_{t,l}$ is Weibull deterioration function parameter for service life adjustment of component type t in location l; $\alpha_{t,l}$ is degradation factor for component type t in location l; $C_{t,l,p}(y)$ is component condition in year y which is calculated based on initial condition $IC_{t,l}$, as shown in Equation (4-10); $TC_{t,l}$ is a terminal condition index value (minimum acceptable condition of components) for component type t in location l; and $ME_{t,l}$ is improvement in condition due to maintenance intervention for component type t in location l. Note that α and β parameters of the Weibull deterioration function depend on the operational and environmental condition of components. These parameters should be determined based on building conditions data and expert opinion.

$$R_{t,l,p}(y) = RC_{t,l} \times \left(\frac{100 - C_{t,l,p}(y)}{100 - TC_{t,l}}\right) \tag{4-11}$$

Where: $R_{t,l,p}(y)$ is the estimated repair cost for RRU plan $P_{t,l,p}$ in year y, and $RC_{t,l}$ is cost of replacement of existing component type t in location l with same product.

4.1.3 Constraints

To ensure that the developed model provides feasible and practical solutions, the optimization model integrates five types of constraints: (1) annual operation and maintenance budget, (2) upgrade and maintenance plan alternative selection, (3) service life of building fixtures and equipment, (4) expectations of building operational performance, and (5) PV system design requirements. The annual budget constraints are integrated into the model to ensure that the operation and maintenance costs of a building do not exceed the available budget for each year. The available budget for each year is specified by the user in addition to any savings from the previous year, as shown in Equation (4-12) and Equation (4-13). Note that a user-specified percentage of the annual budget will be reserved in each year for any unexpected maintenance issues that might arise, such as a broken window, as shown in Equation (4-13).

$$\begin{gathered} AB - RB > TC_1 \\ y \times AB - RB > \sum_{y=1}^{K} TC_y \quad \forall \mathrm{K} = 2, \ldots, Y \end{gathered} \tag{4-12}$$

$$TC_y = \sum_{t=1}^{8}\sum_{l=1}^{NS_t}\sum_{p=1}^{N_{t,l}} P_{t,l,p} \times \left(RRUC_{t,l,p}(y) + OC_{t,l,p}(y)\right) + \sum_{p=1}^{N_c} CS_p \times \left(OCCS_p(y) + RRUCH_p(y) + RRUCC_p(y) + RRUCW_p(y) + RRUCR_p(y) + RRUCG_p(y)\right) + \sum_{p=1}^{N_p} Q_p \times \left(UCQ_p(y) + OCQ_p(y)\right) \tag{4-13}$$

Where: TC_y is total upgrade and maintenance cost in year y that is calculated based on Equation (4-13), RB is a user-specified reserved budget for unexpected maintenance issues, AB is available annual budget, and Y is number of years of a predefined period of study.

The building upgrade and maintenance plan alternative selection constraints are designed to limit the optimization model to select only one plan from the feasible set of plans, as shown in Equation (4-14) to Equation (4-16).

$$\sum_{p=1}^{N_{t,l}} P_{t,l,p} = 1 \qquad \forall\, t = 1, \dots, 8 \quad \forall\, l = 1, \dots, NS_t \tag{4-14}$$

$$\sum_{p=1}^{N_c} CS_p = 1 \tag{4-15}$$

$$\sum_{p=1}^{N_p} Q_p = 1 \tag{4-16}$$

The components' service life constraints are integrated into the model to ensure that building equipment and components are repaired, replaced, or upgraded before their service life end. For example, all building components in all years should have remaining service lives equal or greater than zero for all the years in the study period Y, as shown in Equation (4-17).

$$RSL_{t,l,p}(y) \geq 0 \quad \forall\, t = 1, \dots, 14 \quad \forall\, l = 1, \dots, NS_t \quad \forall y = 1, \dots, Y \tag{4-17}$$

Where $RSL_{t,l,p}(y)$ is the remaining service life of building component $P_{t,l,p}$ in year y of the study period Y.

To ensure that upgraded or replaced items have the required performance and compatibility with the existing function of the building, operational performance constraints are integrated into the model. Moreover, the model is designed to allow defining increase or reduction percentages for the operational building performance to provide flexibility for decision-makers to increase or reduce the performance of the building. For example, the model is capable of upgrading water heaters with similar equipment that have equivalent water heating capacity, or equipment with reduced heating capacity based on a predefined and feasible reduction percentage, as shown in Equation (4-18). Similarly, the model is capable of upgrading other equipment or components with products that have equivalent performance, or user-specified performance for space heating and cooling capacity and lighting levels.

$$EWHC_{t,l} * \left[1 - AR_{t,l}\right] \leq WHC_{l,p} \quad \forall\, y = 1, \dots, Y \tag{4-18}$$

Where, $EWHC_{t,l}$ is the capacity of existing water heater at location l of the building, $AR_{t,l}$ is the allowed percentage reduction in capacity of the water heater at location l of the building, and $WHC_{l,p}$ is the capacity of water heater in the year y of RRU plan $P_{7,l,p}$. The solar panels constraint is designed to ensure that the required area for implementation of solar panels does not exceed the roof area, as shown in Equation (4-19).

$$A_p(y) \leq ARA \quad \forall\, p = 1, \dots, N_p \quad \forall\, y = 1, \dots, Y \tag{4-19}$$

Where, $A_p(y)$ is the required area for implementing PV system in year y of upgrade plan p, and ARA is the available roof area for installing PV system.

4.2 Implementation Phase

The developed model is implemented using MATLAB 2019b software in six main steps: (1) specifying model input data; (2) creating comprehensive databases of building products, including fixtures, equipment, and building envelope components that contain product specifications and cost data; (3) generating feasible alternative RRU Plans; (4) performing building energy simulations using OpenStudio; (5) executing model computations using binary linear programming to identify optimal building upgrades and maintenance plans; and (6) generating upgrade and maintenance plans in tabular and graphical formats to highlight recommendations for building upgrade and maintenance interventions for the study period. The following sections discuss each of these steps in more detail.

4.2.1 Model Input

The buildings' input data to execute the present model computations can be collected based on construction documents, energy bills, and as-built drawings. The model input data are designed to include the following: (1) building general information such as location, geometry and spaces, envelope and interior construction, number of full-time occupants and visitors, operational schedule, and operational performance levels; (2) HVAC systems and thermal zones; (3) billing rates for electricity, gas, water, and discount rate. These data are collected to generate an OpenStudio model where they can be used to estimate the energy consumption of HVAC systems and water heaters. Furthermore, spreadsheets are used to collect the following: (1) existing building operational data such as building type, the number of full-time occupants and visitors, current energy and water consumption of building from utility bills, and operational performance levels; (2) financial data such as annual operation and maintenance budget, annual discount rate and escalation in utility rates, billing rates for electricity, and gas and water consumption; and (3) existing building component data such as count of each component in each space, specifications, installation dates, and deterioration conditions. In order to assess the existing conditions of building components, a building condition index (BCI) is used for building components to identify their conditions based on a score that ranges from 0 to 100 (Uzarski and Burley 1997). The model can also consider simpler condition assessment methods such as the direct condition rating method (USACE ERDC-CERL 2007), which can be used for non-structural building components such as wall insulation. Direct condition rating uses visual inspections to evaluate building components based on nine condition categories, including Red, Amber, and Green, where each rating category is divided into three classes denoted by high (+), low (-), and middle. Each of these classes corresponds to a value between 0 to 100 as demonstrated in USACE ERDC-CERL (2007).

4.2.2 Data Bases of Building Products

To facilitate data collection of existing building fixtures and equipment as well as identifying an optimal selection of building upgrade and maintenance plans, the model integrates databases of building products. The databases are designed to include data on energy efficient fixtures and equipment, water efficient fixtures, and building envelope components. Energy efficient fixtures and equipment include lighting bulbs, motion sensors, hand dryers, water heaters, vending machines, elevators, HVAC systems, and PV systems. Water efficient fixtures include water faucets, urinals, and toilets. Envelope components include wall insulation, roof insulation, and window glazing and films. The model is designed to search products in the databases to identify feasible alternatives for the existing components. These databases are designed to store data of the above products, including (1) commercial information of products such as brand name and model number, unit price, and vendor name and website; (2) product specifications and operational characteristics such as life expectancy, and energy and water consumption data; and (3) installation costs of building components based on RSMeans building construction cost data (RSMeans 2020). To collect and update the integrated building product databases, a data collection module is developed in MATLAB to automatically fetch the above product data from vendor and supplier websites such as Home Depot. Note that the data collection module is customized based on vendors' websites as there is no common standard for suppliers to present and detail their products. The above module is designed to update the databases periodically, such as monthly. To update the existing data, the data collection module uses the stored product names and URLs to update their commercial information such as their unit price and availability. Moreover, the developed module is capable of searching the vendors' websites to identify new products as they become available. Note that the unit cost of large equipment such as HVAC equipment is challenging to obtain due to the unavailability of data in online sources. Therefore, the authors reached out to a few vendors to receive quotes for equipment costs as needed for the database. Ensuring that the products in the databases are current enables the model to generate up-to-date and practical solutions. Accordingly, this optimization model is expected to bridge the gap between (1) building owners and operators that continuously search for solutions to upgrade their buildings, and (2) vendors and suppliers that offer efficient products for the operation of existing buildings.

4.2.3 Data Preprocessing

Based on the operational performance and service life constraints, the model searches the integrated databases for feasible alternative products and creates a set of RRU alternative plans for every building component. Next, the annual RRU cost, operational cost, and EAOMC of these RRU plans are calculated and stored in a database where they can be recalled during the optimization computations. Moreover, all the feasible scenarios for the combination of HVAC systems, wall insulation, roof insulation, and glazing alternative RRU plans are identified and stored in a database where they can be used during the energy simulation phase and before running the optimization model computations.

The present model uses OpenStudio software to calculate cooling and heating energy consumption. In the first step, the model identifies all feasible combination scenarios of existing components and alternative upgrades for HVAC equipment, wall insulation, roof insulation, and window glazing and films. Next, MATLAB software generates OpenStudio measures with the input arguments based on the specifications of feasible alternatives. Then, the model uses OpenStudio Command Line Interface (OSCLI) to apply those measures to the seed building model. Finally, energy simulation is performed, and energy simulation results are stored in a database where they can be recalled during the optimization computations. Similarly, the present model is designed to identify feasible alternatives for water heaters and use OpenStudio to calculate their annual energy consumption. Note that the present model analyzes the replacement of existing HVAC system components and water heaters with comparable equipment.

4.2.4 Model Computations

After performing energy simulations of alternatives for combinations of HVAC systems and building envelope components, and generating RRU alternative plans for all building components, the model formulates the decision variables, constraints, and objective functions. The optimization model uses binary linear programming to execute its computations due to its capability of (1) modeling the objective function and constraints using linear functions, and (2) identifying global optimum solutions in a short computational time. The model formulation is coded in MATLAB2019b and the model computations are executed using mixed integer linear programming (MILP) solver of Gurobi (GUROBI 2020).

4.2.5 Model Output

The present model is designed to generate its output data in chart and action report formats. The output data include: (1) action reports that summarize detailed recommendations for upgrade and maintenance interventions within the specified study period and annual operation and maintenance budget; (2) economic charts of recommended building upgrade and maintenance plans such as annual costs, savings, and EAOMC during the study period; and (3) charts of buildings' annual operation and maintenance costs during the study period.

5. Case Studies

5.1 Bridge Maintenance System Evaluation

5.1.1 Machine Learning Model

Preprocessing is performed in the initial step to prepare the data for the development of machine learning (ML) models. In the present study, based on NBI and NBE databases, data of concrete bridges located in Colorado from 2014 to 2022 are extracted and concatenated to objectively evaluate the importance of the factors affecting concrete bridge element deterioration. This time frame was chosen as NBE data are only available after 2014. Using item 43 from the NBI, which categorizes the main structure type, concrete bridges with main structure types of "concrete," "concrete continuous," "prestressed concrete," and "prestressed concrete continuous" were selected, resulting in 5,576 unique concrete bridges, representing 62.5% of all bridges in Colorado. The identification number of the selected concrete bridges in the NBI was used to measure the frequency of constituent elements from the NBE to identify the most frequent concrete bridge elements. The most common elements—including reinforced concrete deck, reinforced concrete top flange, prestressed concrete closed web/box girder, prestressed concrete girder/beam, reinforced concrete column, reinforced concrete pier wall, reinforced concrete abutment, reinforced concrete pier cap, reinforced concrete culvert, strip seal joint, pourable joint, steel bridge rail, reinforced concrete bridge rail, wearing surfaces, and steel protective coating—were selected for analysis, as shown in Table 5.1. The NBI and NBE databases were then concatenated using the bridge identification number and year of inspections to generate a comprehensive and uniform database. The NBI contains data on bridge design, specification, operational data, and condition rating of primary components, such as deck, superstructure, and substructure. Out of 142 features reported in the NBI, 72 features that have no impact on bridge element deterioration were eliminated. For example, item 19, which specifies the bypass/detour length, was removed as it does not affect deterioration of the bridge elements. Furthermore, 15 features that report similar information were removed to minimize multicollinearity among the predictor features. For example, item 9, which reports the location of bridges, was eliminated as it reports the same information as items 16 and 17, longitude and latitude, respectively. Additionally, nine features related to NBI condition ratings and inspections were removed as the objective of the study is to predict the HI based on factors affecting bridge deterioration. After removing the redundant features in the preprocessing step, 46 features were kept for the feature selection step. In the final step of preprocessing, the numeric data were standardized using the standard scaler, and categorical data were encoded using "one-hot encoding."

Table 5.1 Percent frequency of common concrete bridge elements in Colorado

Number	NBE Element Number	Description	Element Count	Frequency Percentage
1	215	Reinforced Concrete Abutment	3,903	70%
2	515	Steel Protective Coating	3,883	70%
3	330	Steel Bridge Rail	3,867	69%
4	510	Wearing Surfaces	3,280	59%
5	12	Reinforced Concrete Deck	2,818	51%
6	109	Prestressed Concrete Girder/Beam	1,882	34%
7	234	Reinforced Concrete Pier Cap	1,731	31%
8	241	Reinforced Concrete Culvert	1,622	29%
9	301	Pourable Joint	1,575	28%
10	331	Reinforced Concrete Bridge Rail	1,156	21%
11	205	Reinforced Concrete Column	1,092	20%
12	210	Reinforced Concrete Pier Wall	1,047	19%
13	16	Reinforced Concrete Top Flange	937	17%
14	300	Strip Seal Joint	922	17%
15	104	Prestressed Concrete Closed Web/Box Girder	874	16%

In the present study, the KNN-based mutual information (MI) approach was utilized to identify the features that have the highest impact on the health index (HI) of each bridge element. To this end, National Bridge Inventory (NBI) and National Bridge Element (NBE) data are analyzed. The accuracy of the KNN-based approach is dependent on the selected value of k. However, there is no established method for determining the optimal value of k for the KNN approach (Suzuki et al. 2008). To account for this, a range of k values from 3 to 20 were tested and the ranking of the variables for each of the bridge elements remained consistent. MI represents the amount of information that a specific feature can provide about the target variable and is measured in bits. The calculated MI values for each element were then normalized by the entropy of the HI of the element, also measured in bits, to quantify how much a known feature can reduce the uncertainty in the prediction of HI. The resulting unitless values of "bits/bits" were used to create a heat map of the top 20 features and their normalized MI for each element, as shown in Figure 5.1. The features with normalized MI values above 2% were selected to develop the ML models. Note that the 2% threshold was determined through a trial-and-error process to ensure the highest predictive performance of the models.

The results of the analysis indicate that several factors have a significant impact on the deterioration of various bridge elements. Age is found to have the strongest MI with the deterioration of reinforced concrete abutments, steel protective coatings, steel bridge rails, wearing surfaces, reinforced concrete decks, prestressed concrete girders/beams, reinforced concrete pier caps, pourable joints, reinforced concrete bridge rails, reinforced concrete columns, reinforced concrete pier walls, reinforced concrete top flanges, strip seal joints, prestressed concrete closed web/box girders, and reinforced concrete girders/beams. Latitude and longitude also have significant impact on the deterioration of various bridge elements. Longitude has the strongest MI with the deterioration of reinforced concrete abutments, steel protective coatings, steel bridge rails, wearing surfaces, reinforced concrete decks, prestressed concrete girders/beams, reinforced concrete pier caps, pourable joints, reinforced concrete bridge rails, reinforced concrete columns, reinforced concrete pier walls, reinforced concrete top flanges, strip seal joints, prestressed concrete closed web/box girders, and reinforced concrete girders/beams, as shown in Figure 5.1. This correlation may be attributed to various factors related to climate and weather that can contribute to bridge component deterioration. For example, temperature fluctuations and exposure to moisture and humidity can cause concrete to expand and contract, leading to cracks and other forms of damage over time. Structure length and length of maximum span are found to have a considerable MI with the deterioration of various bridge elements. Structure length is found to have the strongest MI with the deterioration of steel protective coatings, steel bridge rails, reinforced concrete decks, prestressed concrete girders/beams, reinforced concrete pier caps, and reinforced concrete bridge rails, as shown in Figure 5.1. The length of maximum span is found to have the strongest MI with the deterioration of steel protective coatings, steel bridge rails, reinforced concrete decks, prestressed concrete girders/beams, reinforced concrete pier caps, reinforced concrete bridge rails, and reinforced concrete columns, as shown in Figure 5.1. Moreover, average daily traffic is found to have the strongest MI with the deterioration of steel protective coatings, steel bridge rails, and reinforced concrete decks, as shown in Figure 5.1. Operating rating is found to have the strongest MI with the deterioration of steel protective coatings, steel bridge rails, and reinforced concrete decks, as shown in Figure 5.1. Additionally, the results of the analysis revealed that the type of wearing surface has a significant impact on the HI of the reinforced concrete deck element, as shown in Figure 5.1. The analysis showed that the type of wearing surface was the most influential factor in determining the deterioration of this element. Similarly, the bridge roadway width was found to be a major factor influencing the HI of the reinforced concrete pier wall element, as shown in Figure 5.1. Finally, the deck width was identified as a major contributor to the HI of the reinforced concrete girder/beam element, as shown in Figure 5.1.

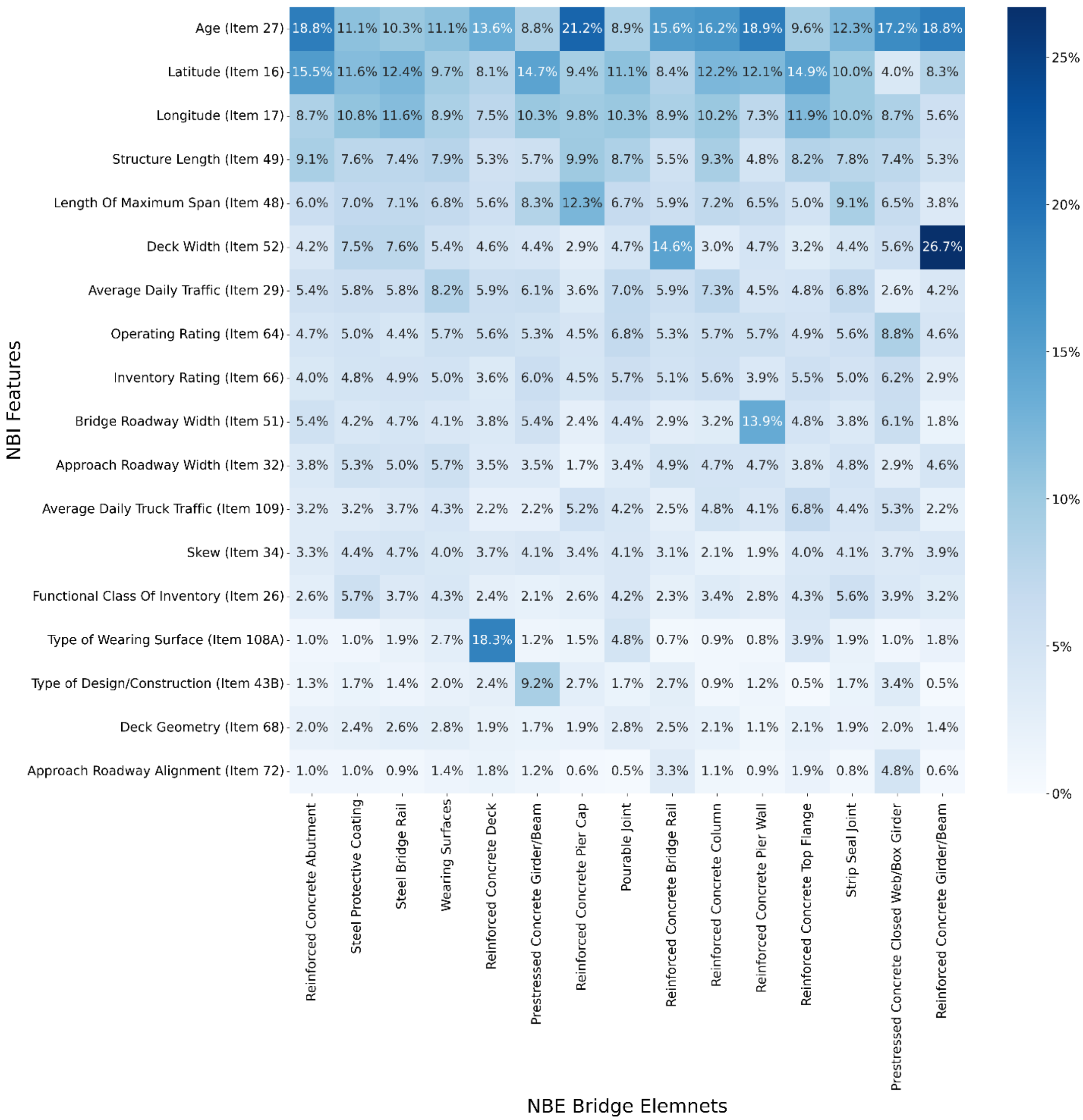

Figure 5.1 Impact of various features on the deterioration of bridge elements

To evaluate the performance of the developed ML models, k-fold (k=5) cross validation is used. In this process, the data are divided into k exclusive subsets, where k is set to 5, and each model is trained on k-1 subsets (80% of data) and tested on the remaining subset (20% of data) in each iteration. This approach provides a distribution of errors that assesses the general applicability of the model to represent the variation in the dataset. Additionally, four common evaluation metrics, including MAE, MSE, MAPE, and R^2, are applied to evaluate the predictive performance of the models, as shown in Table 5.2. The values of predictive performance metrics vary over different elements, but a similar ranking of models can be observed. Based on the results of predictive performance metrics, the random forest (RF) method has the best performance in terms of MAE, MSE, MAPE, and R^2 metrics for all the elements. For example, RF has the best performance in predicting the HI of reinforced concrete deck with MAE, MAPE, MSE, and R^2 with values of 0.015, 2.035%, 0.003, and 0.760, respectively. The MAE metric indicates that RF has the lowest prediction uniform error across the dataset compared with other methods. The MAPE metric indicates that RF has the lowest relative error with respect to the magnitude of target values. Similarly, the MSE metric indicates that RF has the best performance with respect to the magnitude of errors. R^2 metric indicates that, among the tested models, RF can best explain the variance of the HI for each of the elements. Finally, based on the aforementioned results, RF was selected to predict the deterioration of bridge elements in the optimization model due to its accuracy in predicting conditions of bridge elements.

Table 5.2 Predictive performance of the developed ML models

NBE Element Number	Element Name	Model	MAE	MAPE	MSE	R^2
12	Reinforced Concrete Deck	RF	0.015	2.035%	0.003	0.760
		DT	0.017	2.245%	0.004	0.656
		GB	0.017	2.372%	0.003	0.781
		SVM	0.071	7.953%	0.007	0.419
16	Reinforced Concrete Top Flange	RF	0.013	1.710%	0.002	0.841
		GB	0.014	1.861%	0.002	0.850
		DT	0.015	1.975%	0.003	0.751
		SVM	0.067	7.475%	0.006	0.479
104	Prestressed Concrete Closed Web/Box Girder	RF	0.006	0.686%	0.001	0.710
		DT	0.006	0.694%	0.001	0.647
		GB	0.006	0.781%	0.001	0.730
		SVM	0.068	7.040%	0.005	0.338
109	Prestressed Concrete Girder/Beam	RF	0.011	1.482%	0.002	0.745
		DT	0.011	1.557%	0.002	0.668
		GB	0.012	1.662%	0.002	0.761
		SVM	0.073	7.892%	0.007	0.134
110	Reinforced Concrete Girder/Beam	RF	0.007	0.898%	0.001	0.874
		DT	0.007	0.905%	0.001	0.835
		GB	0.007	0.928%	0.001	0.884
		SVM	0.075	7.913%	0.006	0.191
205	Reinforced Concrete Column	RF	0.016	2.056%	0.003	0.799
		DT	0.016	2.104%	0.003	0.743
		GB	0.018	2.367%	0.002	0.817
		SVM	0.078	8.632%	0.008	0.404
210	Reinforced Concrete Pier Wall	DT	0.011	1.440%	0.002	0.792
		RF	0.011	1.440%	0.002	0.827
		GB	0.013	1.727%	0.002	0.838
		SVM	0.077	8.361%	0.007	0.342
215	Reinforced Concrete Abutment	RF	0.015	1.999%	0.002	0.798
		DT	0.016	2.095%	0.003	0.739
		GB	0.017	2.305%	0.002	0.827
		SVM	0.074	8.408%	0.007	0.378
234		RF	0.008	1.116%	0.001	0.907

	Reinforced Concrete Pier Cap	DT	0.009	1.168%	0.001	0.875
		GB	0.009	1.174%	0.001	0.914
		SVM	0.069	7.396%	0.006	0.511
300	Strip Seal Joint	RF	0.058	8.918%	0.015	0.564
		GB	0.060	9.198%	0.012	0.644
		DT	0.062	9.290%	0.021	0.384
		SVM	0.092	13.808%	0.015	0.536
301	Pourable Joint	RF	0.040	7.399%	0.011	0.659
		GB	0.043	7.974%	0.009	0.709
		DT	0.044	7.814%	0.015	0.524
		SVM	0.088	12.700%	0.013	0.573
330	Steel Bridge Rail	RF	0.011	1.679%	0.003	0.796
		DT	0.012	1.765%	0.003	0.738
		GB	0.014	2.008%	0.002	0.822
		SVM	0.076	8.369%	0.007	0.415
331	Reinforced Concrete Bridge Rail	RF	0.022	3.064%	0.004	0.746
		DT	0.023	3.202%	0.005	0.669
		GB	0.026	3.561%	0.004	0.771
		SVM	0.077	9.003%	0.008	0.455
510	Wearing Surfaces	RF	0.022	3.070%	0.004	0.651
		GB	0.024	3.383%	0.004	0.698
		DT	0.024	3.338%	0.006	0.526
		SVM	0.074	8.535%	0.008	0.366
515	Steel Protective Coating	RF	0.016	3.371%	0.005	0.745
		DT	0.017	3.482%	0.006	0.683
		GB	0.020	3.954%	0.004	0.772
		SVM	0.080	9.885%	0.009	0.500

5.1.2 Optimization Results

A case study of a concrete bridge located in Colorado is analyzed to illustrate the use of the developed system and demonstrate its unique capabilities. The bridge was constructed in 2004 with the primary function of facilitating vehicular traffic and pedestrian walkway passage over the Coal Creek waterway with average daily traffic (ADT) of 5,245 vehicles. The bridge is classified as a local route and has a total length of 264.1 feet (80.5 meters) with the largest span measuring 128.3 feet (39.1 meters). The bridge comprises two main spans constructed using prestressed concrete. The main spans are designed using the stringer/multi-beam and the deck type is concrete cast-in-place with a bituminous wearing surface. The optimization model is used to identify the optimal maintenance interventions for all the bridge elements, including reinforced concrete deck, prestressed concrete beams, reinforced concrete columns, reinforced concrete abutments, reinforced concrete piers, strip seal expansion joints, pourable joint seals, steel bridge rail, reinforced concrete bridge rail, wearing surfaces, and steel protective coating.

The case study input data are facilitated using NBI and NBE datasets to perform the present optimization analysis. The collected data include information on the bridge's characteristics, such as bridge type, age, location, design and materials, and geometry, as well as operational data such as ADT and inventory rating. Additionally, data on specific bridge elements, including the quantity and condition of each element as determined by HI ratings, are inputted into the model. A sample of the input data that summarize the main bridge characteristics is shown in Table 5.3. Note that the importance weight for each bridge element is calculated based on the cost of replacement and reconstruction for that element in relation to the sum of the cost of replacement and reconstruction for all elements, as shown in Table 5.3. Additionally, the terminal HI, which represents the minimum acceptable condition for each element, is set at 40% for all bridge elements. Based on the collected input data, the HI of each bridge element in the case study was predicted for each year over the study period, using a multi-step forecasting method and the developed RF models.

Table 5.3 Summary of the case study bridge characteristics

Element Group	NBE Element Number	Element Name	Unit	Quantity	Existing Health Index	Element Importance Weight
Deck/Slab	12	Reinforced Concrete Deck	SF	12,672	99.97	68.17%
Superstructure	109	Prestressed Concrete Girder/Beam	LF	1,584	93.4	20.45%
Substructure	205	Reinforced Concrete Column	LF	72	100	0.17%
Substructure	215	Reinforced Concrete Abutment	LF	96	97.92	3.22%
Substructure	234	Reinforced Concrete Pier Cap	LF	48	100	0.62%
Joint	300	Strip Seal Expansion Joint	LF	96	67	0.62%
Joint	301	Pourable Joint Seal	LF	96	33	0.25%
Bridge Rail	330	Steel Bridge Rail	LF	792	99.58	1.70%
Bridge Rail	331	Reinforced Concrete Bridge Rail	LF	528	97.99	1.70%
Wearing Surfaces and Protective Coatings	510	Wearing Surfaces	SF	9,504	50	3.07%
Wearing Surfaces and Protective Coatings	515	Steel Protective Coating	SF	792	98.74	0.03%

The present system is used to maximize average performance of the case study bridge over a 50-year study period while complying with annual budgets that ranged from \$26,000 to \$125,000. The \$26,000 annual budget is the minimum budget to maintain the conditions of the bridge elements above the specified terminal health index of 40% during the study period. The case study results demonstrate that the system effectively identifies the optimal set of maintenance interventions for all specified annual budgets, as shown in Figure 5.2. The results of the optimization model reveal that as the annual budget for bridge maintenance increases, the average performance index of the bridge improves. However, as the budget increases, the rate at which the performance index improves decreases. This indicates that the model has the resources to implement additional maintenance interventions which, although they still improve the bridge condition index, have less significant impact. For example, increasing the budget from \$50,000 to \$75,000 results in an 8.17% increase in the average performance index (i.e., 74.87% to 83.03%), while increasing the budget from \$100,000 to \$125,000 results in a 5.31% increase (i.e., 91.32% to 96.63%), as shown in Figure 5.2. The model is designed to generate diagrams to illustrate the impact of different annual budgets on the bridge performance and cumulative maintenance costs over time, as shown in Figure 5.3 and Figure 5.4, respectively. These figures show that the model gradually spends the available budgets to prevent the degradation of bridge elements. As the annual budget increases, more costly maintenance interventions can be implemented, resulting in a greater impact on the average performance index. Conversely, with lower budgets, the model is restricted in scheduling costly maintenance interventions, leading to a greater degradation of the performance index, as shown in Figure 5.3 and Figure 5.4.

The optimization computations were conducted on a personal computer with an Intel Core i7 processor at 2.3 GHz and 8GB of RAM. The optimization computations for the above annual budgets were executed on average in 45 minutes. Based on the optimization model output, for each of the specified budgets, an action report is generated in order to provide detailed recommendations for maintenance interventions within the specified annual budget. A sample of items in the action report for the annual budget of $75K is shown in Table 5.4.

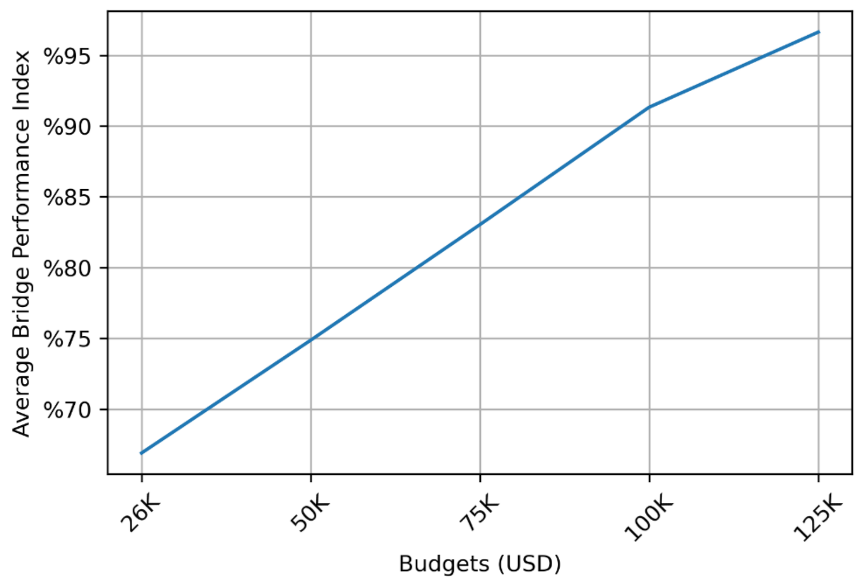

Figure 5.2 Average bridge performance for specified annual budgets ranging from $26K to $150K

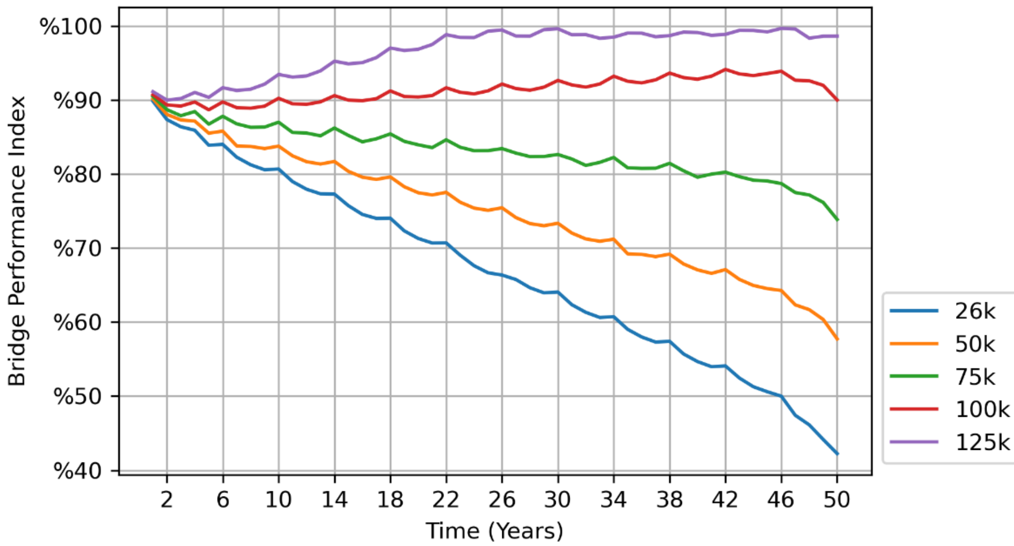

Figure 5.3 Bridge performance over time under various annual maintenance budgets

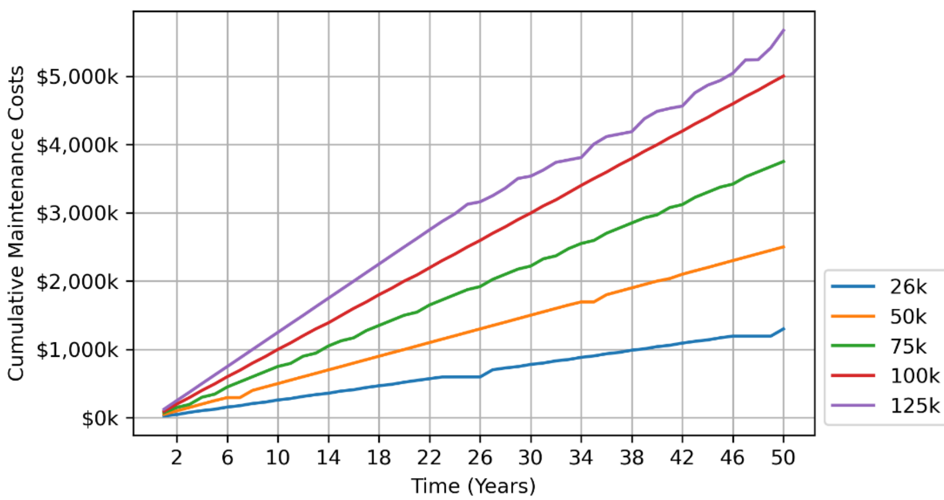

Figure 5.4 Cumulative maintenance costs over time for various maintenance budgets

Table 5.4 Sample of action report for the annual budget of $75K: the initial two maintenance interventions and their associated costs

EN	Element	Repair Description	Unit	Intervention 1			Intervention 2		
				Year	Quantity of repair	Cost (USD)	Year	Quantity of repair	Cost (USD)
12	Reinforced Concrete Deck	Seal deck overlays	SF	7	253	105,600	12	760	316,800
109	Prestressed Concrete Girder/Beam	Patch or fill any cracks or damage to the concrete surface.	LF	1	32	31,680	2	95	95,040
205	Reinforced Concrete Column	Patch or fill any cracks or damage to the concrete surface.	LF	7	3	533	11	1	267
215	Reinforced Concrete Abutment	Patch or fill any cracks or damage to the concrete surface.	LF	23	17	44,928	35	4	9,984
234	Reinforced Concrete Pier Cap	Patch or fill any cracks or damage to the concrete surface.	LF	24	1	960	37	1	960
300	Strip Seal Joint	Repair or replace the sealant in the joint to prevent water infiltration	LF	1	12	5,760	2	2	960
301	Pourable Joint	Repair or replace the sealant in the joint to prevent water infiltration	LF	1	31	6,144	6	4	768
330	Steel Bridge Rail	Repair or replacement of damaged components and tightening or replacing loose bolts	LF	23	63	10,560	37	16	2,640
331	Reinforced Concrete Bridge Rail	Patch or fill any cracks or damage to the concrete surface.	LF	6	21	5,280	23	11	2,640
510	Wearing Surfaces	Patch or fill any cracks or potholes on the surface	SF	3	950	23,760	4	3,231	80,784
515	Steel Protective Coating	Fill in small areas of damage or apply a new coat over the existing one to extend the life of the coating.	SF	1	32	79	2	174	436

5.2 Upgrade And Maintenance Optimization Model for Buildings

5.2.1 Simulated Highway Rest Area Building

To evaluate the upgrade and maintenance optimization model, a hypothetical case study was conducted using a highway rest area building. Due to the unavailability of data in the local DOT, hypothetical data were used for the analysis, which is representative of a real case study presented in Abdallah et al. (2016). The assumption is made to ensure that the analysis conducted using the hypothetical data can provide valuable insights for real-world applications. The building analyzed has a total area of 3,575 feet and approximately 840,000 annual visitors. The rest area building consists of a lobby, women's bathroom, men's bathroom, mechanical room, storage room, travel information desk, and technician's office. Additionally, the building has a parking lot that accommodates cars and semi-trucks, a large landscaped area, and outdoor picnic tables. The equipment and systems that have the highest share of operational costs in the building include interior and exterior lighting, HVAC systems, water heaters, hand dryers, vending machines, water coolers, personal computers, surveillance systems, water faucets, urinals, and toilets.

The input data for this analysis include: (1) building characteristics, such as construction materials, which are presented in Table 5.5; (2) specifications, conditions, and count of existing components in all areas of the building, as presented in Table 5.6; and (3) billing and escalation rates for electricity, gas, and water, as well as the discount rate, which are presented in Table 5.7. Based on the case study presented in Abdallah et al. (2015), an OpenStudio energy simulation model is developed to calculate energy consumption of cooling and heating systems and water heaters.

Table 5.5 Sample of building characteristics

Title	Description
Building operation schedule	24 hours
Allocation of building activities	31.9% lobby, 6.8% office, 13.1% mechanical and electrical room, 26.6% rest rooms, 12.2% storage, and 9.4% retail sales.
Temperature set and airflow	68°F cooling, and 72°F heating, and minimum design flow of 0.5 cfm/ft2.
Building envelope (roof surfaces)	Wood advanced frame 24" with dark brown shingle roofing and R-19 batt.
Building envelope (above grade walls)	8" CMU with brick exterior finishing, perlite filling, and R-6 wood furred insulation.
Building infiltration	1.36 ACH for perimeter
Building interior construction	Lay-in acoustic tile flooring with R-19 batt, wood standard framing with no board insulation, and mass interior walls.
Doors	7'×6' air-lock entry with single bronze 1/8 in. glass in the north side of the building, 7'×6' door with single 1/8 in. bronze glass in the south side of the building, and two 7'×6' opaque doors with steel hollow core.
Windows	30% single bronze 1/8 in. glass in north, east, and west sides of the building.

Table 5.6 A sample of building input data

t	Equipment Type	l	Space	Existing Equipment ID	Existing Component	Count of Equipment t in space l	Installation Date	Condition
1	Light Bulbs	1	Travel Information Room	22	T8 Linear Lamps of 32 Watts and 2,655 Lumens	5	2018	N/A
5	Toilets	7	Women's Restrooms	5	Toilet of 3.5 gallons per flush	17	2018	55
7	Water Heaters	9	Mechanical Room	7	100K BTU natural gas water Heater with thermal efficiency of 0.8	1	2018	60

Table 5.7 Building utility and discount rates

Description	Rate
Average electricity billing rate	0.107 $/kWh
Average gas billing rate	0.8 $/therms
Average water billing rate	0.0034 $/Gallons
Discount rate	2%
Escalation in electricity rates[1]	1.2%
Escalation in natural gas rates[2]	0.14 %
Escalation in water rates[3]	4.1%

[1&2] (EIA 2021)
[3] (DOE 2019)

5.2.2 Optimization Results

Based on the building input data, the model identifies feasible interventions and generates binary decision variables for RRU plans of all fixtures and equipment. The optimization model is used to minimize EAOMC of the case study building for a 20-year study period while considering various annual operation and maintenance budgets that ranged from $60K to $90K. Note that $60K is identified as the lowest optimized budget to cover operation and maintenance costs of the building during the study period. However, the conventional maintenance (CM) method where fixtures and equipment are replaced with similar products at the end of their service lives requires an annual budget of $65K.

The present model was able to identify the optimal building upgrade and maintenance plans for all the specified annual budgets that resulted in substantial savings and reduction in EAOMC compared with the CM, as shown in Figure 5.5. To report the value of the present model, the results of the various upgrade budgets are compared with the CM, as shown Table 5.8. For example, the model identified an upgrade and maintenance plan for an annual budget of $65K, which results in a 31.78% reduction in EAOMC compared with the CM, and $220,682 (24%) reduction in cumulative total cost at the end of the study period compared with the CM, as shown in Table 5.8. Furthermore, the results of the optimization model for the $90K budget are compared with the CM where no optimization is used. The model showed a 32.59% reduction in EAOMC and $256,785 (29.5%) reduction in cumulative total cost at the end of the study period, as shown in Table 5.8. This highlights the importance of the optimization model where decision-makers and operators can achieve significant savings on operation and maintenance costs of existing buildings with efficient and optimized plans for maintenance and upgrades.

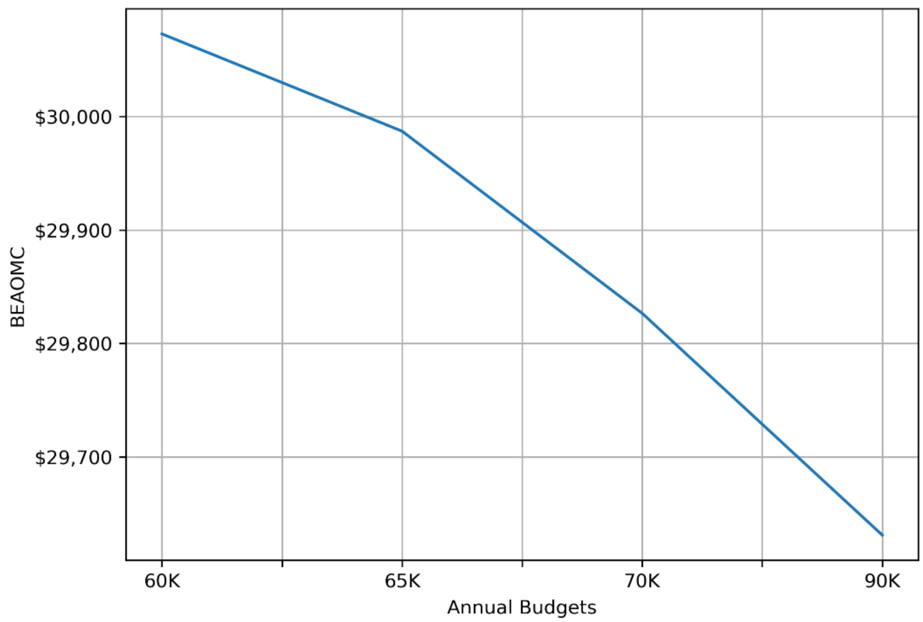

Figure 5.5 EAOMC for a study period of 20 years for budgets of $60K to $90K

Table 5.8 EAOMC and savings for specified annual budgets

Annual Budgets	EAOMC	Reduction in EAOMC Compared to CM	Total savings on operational and RRU costs at the end of the study period (y=20 years)
CM($65,000)	$43,955	NA	NA
$60,000	$30,072	31.58%	$208,838
$65,000	$29,987	31.78%	$220,682
$70,000	$29,827	32.14%	$233,793
$90,000	$29,631	32.59%	$256,785

The model is designed to identify the proper action to replace, repair, or upgrade each fixture and equipment and building component during or at the end of their service lives to minimize EAOMC. Therefore, the model selects different sets of decisions for repair, replace, or upgrade of each building component to comply with the specified annual budget and service life constraints. Consequently, different annual budgets result in different total cumulative RRU costs, as shown in Figure 5.6. The results indicate an inverse relationship between annual budgets and operational costs, as shown in Figure 5.7, where higher annual budgets result in lower operational costs. As an annual budget increases, the model can prioritize more costly upgrades with greater savings in earlier years. Therefore, higher spending on energy- and water-efficient upgrades in initial years results in significant savings on operational costs in the long term, as shown in Figure 5.6 and Figure 5.7. For example, the model gradually upgraded the building with total cumulative RRU cost of $262K for the annual budget of $90K, while the model selected different sets of upgrades with total cumulative RRU cost of $259K for the annual budget of $65K. Although the total cumulative RRU costs for annual budgets of $70K, and $90K are equivalent, as shown in Figure 5.6, the amount of savings on operational costs are different due to different timing of RRU interventions, as shown in Figure 5.7. Specifically, the model achieved savings of $390K and $413K on operational costs for annual budgets of $70K and $90K, respectively.

The results show that the model gradually upgrades the building with energy- and water-efficient components to reduce the operational costs as annual budgets and savings from previous years become available. Therefore, higher investments on upgrades in earlier years resulted in lower cumulative operation and maintenance costs at the end of the study period, as shown in Figure 5.8. For example, an annual budget of $90K results in total cumulative RRU cost of $262K, which is the highest spending on upgrade costs, and total cumulative operational cost of $351K, which is the lowest among other specified budgets.

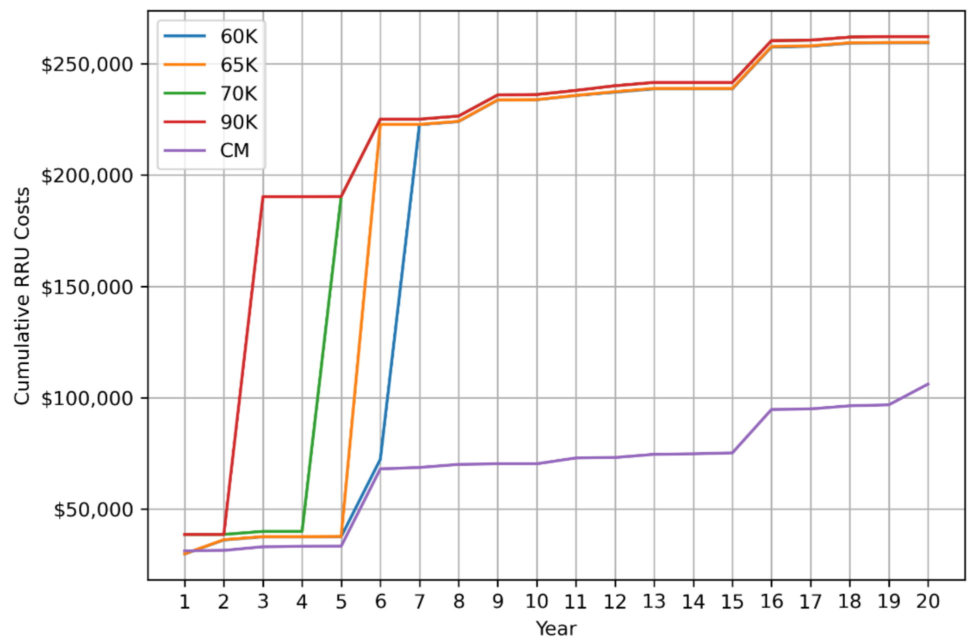

Figure 5.6 Cumulative RRU costs

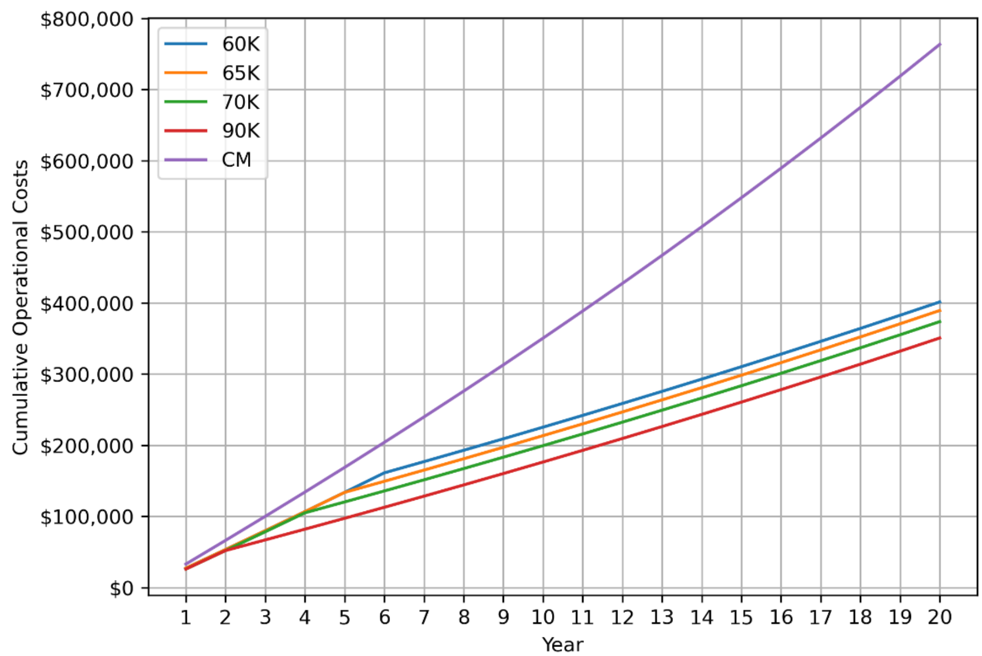

Figure 5.7 Cumulative operational costs for various operational budgets

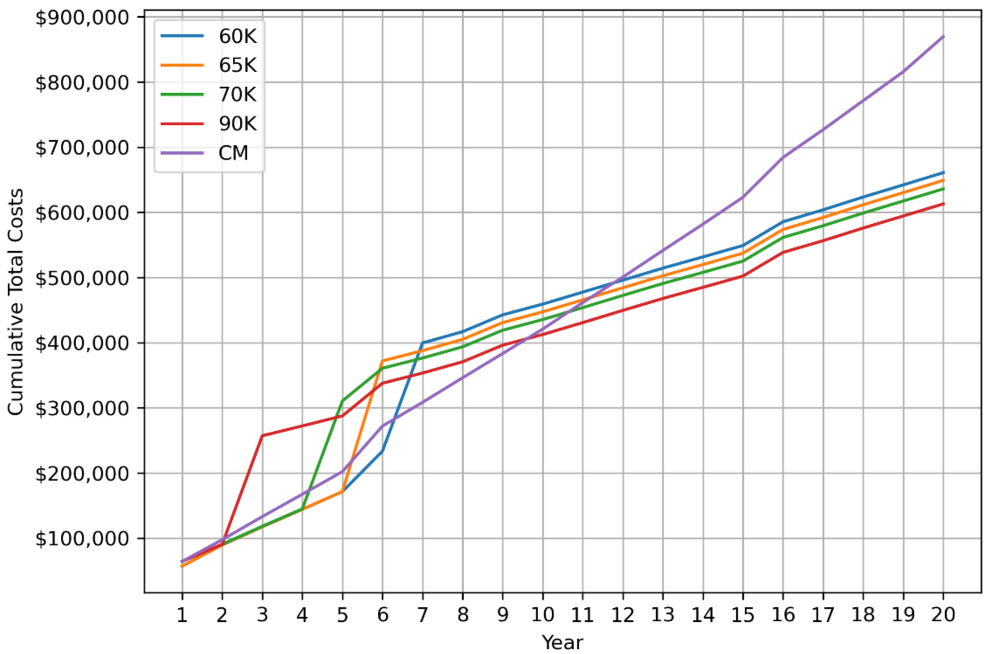

Figure 5.8 Cumulative operation and RRU costs

The optimization computations were performed on a personal computer with Intel Core i7, CPU 2.3 GHz processor, and 8GB RAM. The optimization computations for the above annual budgets were executed in one minute on average. Moreover, the energy simulation for all combinations of HVAC and envelope component alternatives were performed using the same personal computer in four hours, as a preparatory step before optimization. Based on the optimization model output, an action report is generated to provide detailed recommendations for upgrade and maintenance interventions within the specified annual operation and maintenance budget. A sample of items in the action report for the annual operational budget of $65K is shown in Table 5.9. For example, the model recommends upgrading the lighting lamps at location $l = 1$ (Travel Information Room) with more efficient alternatives in the first year and replaces them again with similar lamps at the end of their service lives in year 6, as shown in Table 5.9.

Table 5.9 Example items in an action report for the annual operational budget of $65K

Component Type	l	Space	Existing Component	Interventions			
				Year	Action	Year	Action
Lighting Lamps	1	Travel Information Room	T8 linear lamps of 32 watts and 2,655 lumens	1	Upgrade item: 32-watt equivalent T8 linear LED of 12 watts and 2,790 lumens	6	Replace item: 32-watt equivalent T8 linear LED of 12 watts and 2,790 lumens
Lighting Lamps	2	Lobby	T12 lamps of 40 watts and 3,330 lumens	1	Upgrade item: T12 lamps of 30 watts and 3,213 lumens	6	Replace item: T12 lamps of 30 watts and 3,213 lumens
Toilets	7	Women's Restrooms	Toilet of 3.5 gallons per flush	1	Upgrade item: Electronic flushing toilet with 1.1 gallons per flush	3	Repair item: Repair the existing toilets
Urinals	8	Men's Restrooms	Urinal of 1.6 gallons per flush	1	Upgrade item: Electronic flush urinal of 0.125 gallons per flush	3	Repair item: Repair the existing urinals
Water Heaters	9	Mechanical Room	100K BTU natural gas water heater with thermal efficiency of 0.8	2	100K BTU natural gas water heater with thermal efficiency of 0.85	5	Repair item: Repair the existing water heater
HVAC System	-	N/A	Rooftop air conditioning units with EER of 10.3	4	Rooftop air conditioning units with EER of 15.2	-	-
PV systems	-	Roof	No PV systems	6	Upgrade item: Install PV system with capacity of 100KW	-	-

5.3 Summary and Conclusions

Maintenance interventions for infrastructure and buildings are essential for their long-term sustainability and performance. The selection of optimal maintenance interventions and their timing is crucial for ensuring that they continue to function effectively while minimizing maintenance costs. This research presents the development of two novel systems for optimizing maintenance interventions for bridges and buildings.

The first system is designed to be capable of predicting the condition of concrete bridge elements to identify optimal selection of maintenance interventions and their timing to maximize bridge performance while complying with available annual budgets. The system consists of (1) machine learning (ML) models to predict the condition of concrete bridge elements, and (2) a bridge maintenance optimization model to identify optimal selection of maintenance interventions and their timing. The bridge element deterioration forecasting models are developed in four main steps: data preprocessing where the National Bridge Inventory (NBI) and the National Bridge Elements (NBE) data are concatenated and prepared to be used for ML model development; feature selection where factors affecting deterioration of bridge elements are identified; model development where four different ML models are trained and tested using the selected features from NBI data; and predictive performance evaluation where the predicted data from the test dataset are compared with reported data. The optimization model is developed in three main steps that focus on identifying model decision variables, formulating objective function and constraints, and implementing optimization computations. The optimization model is designed to evaluate the cost-effectiveness of maintenance interventions based on the performance level of bridge elements, as measured by their health index, and the associated maintenance costs over the specified study period. ML methods were selected to predict deterioration of bridge elements due to their capability of predicting non-stationary and nonlinear time series data with high accuracy. Four machine learning methods, decision tree (DT), random forest (RF), gradient boosting (GB), and support vector machines (SVM), were investigated using the NBI and NBE databases to identify the best method for predicting bridge element conditions. Results from the predictive performance evaluation indicated that while the values of the predictive performance metrics varied for different elements, a similar ranking of models was observed. Based on the predictive performance metrics, the RF method had the highest performance in terms of mean absolute error (MAE), mean square error (MSE), mean absolute percentage error (MAPE), and coefficient of determination (R^2 score) metrics for all elements. The computations of the optimization model are performed using binary linear programming due to its capability of identifying global optimum solutions in a short computational time. The case study results showed that the developed model identified optimal maintenance interventions for all the specified annual budgets over a 50-year study period. The main contributions of this system to the body of knowledge are: (1) introducing an innovative system that integrates ML techniques and linear programming for predicting bridge element condition and optimizing maintenance interventions; (2) modeling and predicting the deterioration of bridge elements based on NBE's health index metric; and (3) generating long-term maintenance plans that optimize bridge performance while complying with annual budget constraints. The optimization model provides unique and practical capabilities that enable decision-makers to identify an optimal schedule of bridge maintenance interventions based on available budgets.

The second system is designed to be capable of optimizing the selection of upgrade and maintenance interventions for existing buildings to minimize their equivalent annual operation and maintenance costs (EAOMC) while complying with specified annual budgets and building operational performance constraints. The optimization model is developed in three main phases: (1) identifying model decision variables, formulating objective function and optimization constraints; (2) implementing the model computations using binary linear programming; and (3) analyzing and refining the performance of the optimization model using a case study of a university building. In the formulation phase, the decision variables, objective function, and constraints are identified. The decision variables of the optimization model are designed to represent all feasible plans for repairing, replacing, and upgrading (RRU) building components for a number of years in a study period. The model is integrated with a set of constraints to comply with the annual operation and maintenance budget, component service lives, operational performance, and available area for installing PV systems. The model implementation phase is designed to specify the model input and output data and execute model computations efficiently. The computations of the present model are performed using binary linear programming due to its capability of identifying global optimum solutions in a short computational time. The present model is integrated with expandable databases of building products to facilitate the selection of building components in the input data and to identify the product replacement and upgrade alternatives. A case study of a rest area is analyzed to evaluate the performance of the developed model and illustrate its capabilities. The present model identified optimum building upgrade and maintenance plans for all the specified annual budgets. For the generated solutions, the model provided detailed recommendations for upgrade and maintenance interventions within the specified annual operation and maintenance budget. The primary contributions that this model adds to the body of knowledge are (1) a new computationally efficient and simulation-based methodology to identify optimal selection of building upgrade and maintenance interventions to minimize EAOMC within the available budget, and (2) a new approach for integrating maintenance and upgrade interventions to maximize economic benefits from building operation by reducing operational and maintenance costs. The new capabilities of the model will support decision-makers in maximizing their economic benefits by reducing buildings' energy and water consumption and identifying optimal schedule of upgrade and maintenance interventions with respect to available budgets.

6. REFERENCES

Abdallah, M., El-Rayes, K., and Liu, L. (2016). "Optimizing the selection of sustainability measures to minimize life-cycle cost of existing buildings." *Canadian Journal of Civil Engineering*, NRC Research Press, 43(2), 151–163.

Abdelkader, E. M., Moselhi, O., Marzouk, M., and Zayed, T. (2021). "Integrative Evolutionary-Based Method for Modeling and Optimizing Budget Assignment of Bridge Maintenance Priorities." *Journal of Construction Engineering and Management*, 147(9).

Alogdianakis, F., Dimitriou, L., and Charmpis, D. C. (2021). "Pattern Recognition in Road Bridges' Deterioration Mechanism: An Artificial Approach for Analysing the US National Bridge Inventory." *Transportation Research Procedia*, Elsevier B.V., 52(2020), 187–194.

Alonso Medina, P., León González, F. J., and Todisco, L. (2022). "Data-driven prediction of long-term deterioration of RC bridges." *Construction and Building Materials*, 317.

Althaqafi, E., and Chou, E. (2022). "Developing Bridge Deterioration Models Using an Artificial Neural Network." *Infrastructures*, 7(8).

Amini, A., Nikraz, N., and Fathizadeh, A. (2016). "Identifying and evaluating the effective parameters in prioritization of urban roadway bridges for maintenance operations." *Australian Journal of Civil Engineering*, Taylor and Francis Ltd., 14(1), 23–34.

Amini Toosi, H., Lavagna, M., Leonforte, F., Del Pero, C., and Aste, N. (2020). "Life Cycle Sustainability Assessment in Building Energy Retrofitting; A Review." *Sustainable Cities and Society*, Elsevier, 60 (May), 102248.

Arpke, A., and Hutzler, N. (2005). "Operational life-cycle assessment and life-cycle cost analysis for water use in multioccupant buildings." *Journal of Architectural Engineering*, 11(3), 99–109.

AWWA. (2019). *2019 Water and Wastewater Rate Survey*. American Water Works Association.

Baldoni, E., Coderoni, S., D'Orazio, M., Di Giuseppe, E., and Esposti, R. (2019). "The role of economic and policy variables in energy-efficient retrofitting assessment. A stochastic Life Cycle Costing methodology." *Energy Policy*, Elsevier Ltd, 129 (February), 1207–1219.

Bektas, B. A. (2017). "Use of recursive partitioning to predict national bridge inventory condition ratings from national bridge elements condition data." *Transportation Research Record*, National Research Council, 2612, 29–38.

Bukhsh, Z. A., Stipanovic, I., Palic, S. S., and Klanker, G. (2018). "Robustness of the multi-attribute utility model for bridge maintenance planning." *Baltic Journal of Road and Bridge Engineering*, Riga Technical University, 13(4), 404–415.

Byun, J., Hong, I., Lee, B., and Park, S. (2013). "Intelligent household LED lighting system considering energy efficiency and user satisfaction." *IEEE Transactions on Consumer Electronics*, 59(1), 70–76.

Cahill, R., Lund, J. R., Deoreo, B., and Medellín-Azuara, J. (2013). "Household water use and conservation models using Monte Carlo techniques." *Hydrology and Earth System Sciences*, 17(10), 3957–3967.

Carlsson, M., Touchie, M., and Richman, R. (2019). "Investigating the potential impact of a compartmentalization and ventilation system retrofit strategy on energy use in high-rise residential buildings." *Energy and Buildings*, Elsevier B.V., 199, 20–28.

Chyad, A. M., and Abudayyeh, O. (2020). “Performance Prediction Modeling of Concrete Bridge Deck Condition Using an Optimized Approach.” *Journal of Civil Engineering and Construction*, Tech Reviews Ltd, 9(3), 127–137.

Contreras-Nieto, C., Shan, Y., Lewis, P., and Hartell, J. A. (2019). “Bridge maintenance prioritization using analytic hierarchy process and fusion tables.” *Automation in Construction*, Elsevier, 101 (July 2018), 99–110.

Courville, A., Goodfellow, I., and Bengio, Y. (2016). *Deep Learning.* MIT Press.

Czum, J. M. (2020). “Dive Into Deep Learning. ” *Journal of the American College of Radiology*.

Das, R., and Nakano, M. (2021). “A multi-criteria decision-making model using socio-technical attributes for transportation bridge maintenance prioritisation.” *International Journal of Construction Management*, Taylor & Francis, 0(0), 1–7.

DOE. (2019). “Guidance on Utility Rate Estimations and Weather Normalization in Performance Contracts.” (November 2017).

Echaveguren, T., and Dechent, P. (2019). “Allocation of bridge maintenance costs based on prioritization indexes.” *Revista de la Construccion*, Pontificia Universidad Catolica de Chile, Escuela de Construccion Civil, 18(3), 568–578.

EIA. (2021). “Annual Energy Outlook 2020.” 1–81.

Evin, D., and Ucar, A. (2019). “Energy impact and eco-efficiency of the envelope insulation in residential buildings in Turkey.” *Applied Thermal Engineering*, Elsevier, 154 (December 2018), 573–584.

Evins, R. (2013). “A review of computational optimisation methods applied to sustainable building design.” *Renewable and Sustainable Energy Reviews*, Elsevier, 22, 230–245.

Fantucci, S., and Serra, V. (2019). “Investigating the performance of reflective insulation and low emissivity paints for the energy retrofit of roof attics.” *Energy & Buildings*, Elsevier B.V., 182, 300–310.

Farahani, M. A., Vahid, A., and Goodwell, A. E. (2022). “Evaluating Ecohydrological Model Sensitivity to Input Variability with an Information-Theory-Based Approach.” *Entropy*, 24(7), 1–22.

Fazel, A., Izadi, A., and Azizi, M. (2016). “Low-cost solar thermal based adaptive window : Combination of energy-saving and self-adjustment in buildings.” *Solar Energy*, Elsevier Ltd, 133, 274–282.

FHWA. (1995). *Recording and Coding Guide for the Structure Inventory and Appraisal of the Nation's Bridges.*

FHWA. (2014). *Specification for the National Bridge Inventory*.

FHWA. (2023). “Bridges & Structures - Federal Highway Administration.” *FHWA*, <https://www.fhwa.dot.gov/bridge/> (Jan. 28, 2023).

Fiorillo, G., and Nassif, H. (2019). “Application of Machine Learning Techniques for the Analysis of National Bridge Inventory and Bridge Element Data.” *Transportation Research Record*, 2673(7), 99–110.

Fiorillo, G., and Nassif, H. (2020). “Improving the conversion accuracy between bridge element conditions and NBI ratings using deep convolutional neural networks.” *Structure and Infrastructure Engineering*, Taylor & Francis, 16(12), 1669–1682.

Fitriani, H., Surya Pratama, M. A., Idris, Y., and Tanzil, G. (2019). "Determination of prioritization for maintenance of the upper structure of truss bridge." MATEC Web of Conferences, EDP Sciences, 276, 01036.

Fraher, M. J., Hwang, S., and Fu, J. (2010). "An improved model for predicting NBI condition ratings." Bridge Maintenance, Safety, Management and Life-Cycle Optimization - Proceedings of the 5th International Conference on Bridge Maintenance, Safety and Management, 1039–1043.

Franzen, S. E., Farahani, M. A., and Goodwell, A. E. (2020). "Information Flows: Characterizing Precipitation-Streamflow Dependencies in the Colorado Headwaters With an Information Theory Approach." *Water Resources Research*, 56(10).

Ghodoosi, F., Abu-Samra, S., Zeynalian, M., and Zayed, T. (2018). "Maintenance Cost Optimization for Bridge Structures Using System Reliability Analysis and Genetic Algorithms." *Journal of Construction Engineering and Management*, 144(2).

Goia, F. (2016). "Search for the optimal window-to-wall ratio in office buildings in different European climates and the implications on total energy saving potential." *Solar Energy*, Elsevier Ltd, 132, 467–492.

Gokasar, I., Deveci, M., and Kalan, O. (2022). "CO2 Emission based prioritization of bridge maintenance projects using neutrosophic fuzzy sets based decision making approach." *Research in Transportation Economics*, Elsevier Ltd, 91 (January 2021).

Guardigli, L., Bragadin, M. A., Della Fornace, F., Mazzoli, C., and Prati, D. (2018). "Energy retrofit alternatives and cost-optimal analysis for large public housing stocks." *Energy and Buildings*, Elsevier B.V., 166, 48–59.

Gugliermetti, F., and Bisegna, F. Ã. (2007). "Saving energy in residential buildings : The use of fully reversible windows." 32, 1235–1247.

Gustafsson, M. S., Myhren, J. A., Dotzauer, E., and Gustafsson, M. (2019). "Life cycle cost of building energy renovation measures, considering future energy production scenarios." *Energies*, 12(14).

Hadjidemetriou, G. M., Herrera, M., and Parlikad, A. K. (2022). "Condition and criticality-based predictive maintenance prioritisation for networks of bridges." *Structure and Infrastructure Engineering*, Taylor and Francis Ltd., 18(8), 1207–1221.

Harvey, L. D. D. (2013). "Recent advances in sustainable buildings: Review of the energy and cost performance of the state-of-the-art best practices from around the world." *Annual Review of Environment and Resources*, 38(1), 281–309.

Hasan, S., and Elwakil, E. (2020). "National Bridge Inventory Data-Based Stochastic Modeling for Deck Condition Rating of Prestressed Concrete Bridges." *Practice Periodical on Structural Design and Construction*, 25(3).

Hashempour, N., Taherkhani, R., and Mahdikhani, M. (2020). "Energy performance optimization of existing buildings: A literature review." *Sustainable Cities and Society*, Elsevier, 54 (July 2019), 101967.

Huang, H., Zhou, Y., Huang, R., Wu, H., Sun, Y., and Huang, G. (2020). "Optimum insulation thicknesses and energy conservation of building thermal insulation materials in Chinese zone of humid subtropical climate." *Sustainable Cities and Society*, Elsevier, 52(May 2019), 101840.

Huang, Y.-H., Adams, T. M., and Pincheira, J. A. (2004). "Analysis of Life-Cycle Maintenance Strategies for Concrete Bridge Decks." *Journal of Bridge Engineering*, 9(3).

Jaafaru, H., and Agbelie, B. (2022). “Bridge maintenance planning framework using machine learning, multi-attribute utility theory and evolutionary optimization models.” *Automation in Construction*, Elsevier, 141, 104460.

Jie, P., Yan, F., Li, J., Zhang, Y., and Wen, Z. (2019). “Optimizing the insulation thickness of walls of existing buildings with CHP-based district heating systems.” *Energy*, Elsevier Ltd, 189, 116262.

Jie, P., Zhang, F., Fang, Z., Wang, H., and Zhao, Y. (2018). “Optimizing the insulation thickness of walls and roofs of existing buildings based on primary energy consumption, global cost and pollutant emissions.” *Energy*, Elsevier Ltd, 159, 1132–1147.

Juanicó, L. E. (2020). “Thermal insulation of roofs by using multiple air gaps separated by insulating layers of low infrared emissivity.” 230, 1–10.

Kim, K. H., Nam, M. S., Hwang, H. H., and Ann, K. Y. (2020). “Prediction of remaining life for bridge decks considering deterioration factors and propose of prioritization process for bridge deck maintenance.” *Sustainability (Switzerland)*, 12(24), 1–25.

Kumar, N. M., and Mathew, M. (2018). “Comparative life-cycle cost and GHG emission analysis of five different water heating systems for residential buildings in Australia.” *Beni-Suef University Journal of Basic and Applied Sciences*, Elsevier B.V., 7(4), 748–751.

Lim, H., and Zhai, Z. J. (2017). “Review on stochastic modeling methods for building stock energy prediction.” *Building Simulation*, 10(5), 607–624.

Litti, G., Audenaert, A., and Lavagna, M. (2020). “Life cycle operating energy saving from windows retro fitting in heritage buildings accounting for technical performance decay.” *Journal of Building Engineering*, Elsevier Ltd, 17 (December 2017), 135–153.

Liu, K., and El-Gohary, N. (2020). “Fusing Data Extracted from Bridge Inspection Reports for Enhanced Data-Driven Bridge Deterioration Prediction: A Hybrid Data Fusion Method.” *Journal of Computing in Civil Engineering*, 34(6).

Liu, K., and El-Gohary, N. (2022). “Deep Learning–Based Analytics of Multisource Heterogeneous Bridge Data for Enhanced Data-Driven Bridge Deterioration Prediction.” *Journal of Computing in Civil Engineering*, 36(5), 1–14.

Liu, M., and Frangopol, D. M. (2005). “Balancing Connectivity of Deteriorating Bridge Networks and Long-Term Maintenance Cost through Optimization.” *Journal of Bridge Engineering*, 10(4).

Liu, Y., Liu, T., Ye, S., and Liu, Y. (2018). “Cost-Benefit Analysis for Energy Efficiency Retrofit of Existing Buildings: A Case Study in China.” *Journal of Cleaner Production*, 177, 493–506.

Lu, P., Wang, H., and Tolliver, D. (2019). “Prediction of Bridge Component Ratings Using Ordinal Logistic Regression Model.” *Mathematical Problems in Engineering*, Hindawi Limited, 2019.

Mangan, S. D., and Oral, G. K. (2015). “A study on life cycle assessment of energy retrofit strategies for residential buildings in Turkey.” *Energy Procedia*, Elsevier B.V., 78, 842–847.

Mariano-Hernández, D., Hernández-Callejo, L., Zorita-Lamadrid, A., Duque-Pérez, O., and Santos García, F. (2021). “A review of strategies for building energy management system: Model predictive control, demand side management, optimization, and fault detect & diagnosis.” *Journal of Building Engineering*, 33 (July 2020).

Miner, N., and Alipour, A. (2022). “Bridge Damage, Repair Costs, and Fragilities for Inland Flood Events.” *Journal of Bridge Engineering*, 27(8).

Moschetti, R., and Brattebø, H. (2017). “Combining life cycle environmental and economic assessments in building energy renovation projects.” *Energies*, 10(11).

Murphy, K. P. (2012). *Machine Learning - A Probabilistic Perspective.* The MIT Press.

Nguyen, T. T., and Dinh, K. (2019). “Prediction of bridge deck condition rating based on artificial neural networks.” *Journal of Science and Technology in Civil Engineering (STCE) - NUCE*, Hanoi University of Civil Engineering (HUCE), 13(3), 15–25.

Nili, M. H., Taghaddos, H., and Zahraie, B. (2021). “Integrating discrete event simulation and genetic algorithm optimization for bridge maintenance planning.” *Automation in Construction*, Elsevier B.V., 122 (February 2020), 103513.

Nili, M. H., Zahraie, B., and Taghaddos, H. (2020). “BrDSS: A decision support system for bridge maintenance planning employing bridge information modeling.” *Smart Structures and Systems*, Techno-Press, 26(4), 533–544.

Peng, J., Yang, Y., Bian, H., Zhang, J., and Wang, L. (2022). “Optimisation of maintenance strategy of deteriorating bridges considering sustainability criteria.” *Structure and Infrastructure Engineering*, Taylor and Francis Ltd., 18(3), 395–411.

PNNL. (2011). *Advanced Energy Retrofit Guide*. U.S. Department of Energy.

Pombo, O., Allacker, K., Rivela, B., and Neila, J. (2016). “Sustainability assessment of energy saving measures: A multi-criteria approach for residential buildings retrofitting - A case study of the Spanish housing stock.” *Energy and Buildings*, Elsevier B.V., 116, 384–394.

Qiu, T., Wang, G., Xu, Q., and Ni, G. (2018). “Study on the thermal performance and design method of solar reflective – thermal insulation hybrid system for wall and roof in Shanghai.” *Solar Energy*, Elsevier, 171 (February), 851–862.

Ran, J., and Tang, M. (2018). “Passive cooling of the green roofs combined with night-time ventilation and walls insulation in hot and humid regions.” *Sustainable Cities and Society*, Elsevier, 38 (February), 466–475.

Ran, J., Tang, M., Jiang, L., and Zheng, X. (2017). “Effect of Building Roof Insulation Measures on Indoor Cooling and Energy Saving in Rural Areas in Chongqing.” *Procedia Engineering*, 180, 669–675.

Ross, B. C. (2014). “Mutual information between discrete and continuous data sets.” *PLoS ONE*, 9(2).

RSMeans. (2020). “RS Means Online Database.”

Sabatino, S., Frangopol, D. M., and Dong, Y. (2015). “Sustainability-informed maintenance optimization of highway bridges considering multi-attribute utility and risk attitude.” *Engineering Structures*, Elsevier Ltd, 102, 310–321.

Sanhudo, L., Ramos, N. M. M., Poças Martins, J., Almeida, R. M. S. F., Barreira, E., Simões, M. L., and Cardoso, V. (2018). “Building information modeling for energy retrofitting – A review.” *Renewable and Sustainable Energy Reviews*, Elsevier Ltd, 89 (March), 249–260.

Santamaria Ariza, M., Zambon, I., S. Sousa, H., Campos e Matos, J. A., and Strauss, A. (2020). “Comparison of forecasting models to predict concrete bridge decks performance.” *Structural Concrete*, 21(4).

Saydam, D., and Frangopol, D. M. (2015). “Risk-Based Maintenance Optimization of Deteriorating Bridges.” *Journal of Structural Engineering*, American Society of Civil Engineers (ASCE), 141(4).

Somasundaram, S., Thangavelu, S. R., and Chong, A. (2020). “Improving building efficiency using low-e coating based retrofit.” *Applied Thermal Engineering*, Elsevier Ltd, 115064.

Streicher, K. N., Mennel, S., Chambers, J., Parra, D., and Patel, M. K. (2020). “Cost-effectiveness of large-scale deep energy retrofit packages for residential buildings under different economic assessment approaches.” *Energy and Buildings*, Elsevier B.V., 215, 109870.

Suzuki, T., Sugiyama, M., Sese, J., and Kanamori, T. (2008). “New challenges for feature selection Approximating Mutual Information by Maximum Likelihood Density Ratio Estimation.” JMLR: Workshop and Conference Proceedings, 4(1), 5–20.

Tällberg, R., Petter, B., Loonen, R., Gao, T., and Hamdy, M. (2019). “Comparison of the energy saving potential of adaptive and controllable smart windows : A state-of-the-art review and simulation studies of thermochromic, photochromic and electrochromic technologies.” *Solar Energy Materials and Solar Cells*, Elsevier B.V., 200 (June), 109828.

Tian, Z., Si, B., Shi, X., and Fang, Z. (2019). “An application of Bayesian Network approach for selecting energy efficient HVAC systems.” *Journal of Building Engineering*, Elsevier Ltd, 25 (May), 100796.

Valenzuela, S., de Solminihac, H., and Echaveguren, T. (2010). “Proposal of an Integrated Index for Prioritization of Bridge Maintenance.” *Journal of Bridge Engineering*, American Society of Civil Engineers (ASCE), 15(3), 337–343.

Vilches, A., Garcia-Martinez, A., and Sanchez-Montañes, B. (2017). “Life cycle assessment (LCA) of building refurbishment: A literature review.” *Energy and Buildings*, 135, 286–301.

Wakchaure, S. S., and Jha, K. N. (2011). “Prioritization of bridges for maintenance planning using data envelopment analysis.” *Construction Management and Economics*, 29(9), 957–968.

Wang, T.-K., and Piao, Y. (2019). “Development of BIM-AR-Based Facility Risk Assessment and Maintenance System.” *Journal of Performance of Constructed Facilities*, 33(6), 04019068.

Xie, H. B., Wu, W. J., and Wang, Y. F. (2018). “Life-time reliability based optimization of bridge maintenance strategy considering LCA and LCC.” *Journal of Cleaner Production*, Elsevier Ltd, 176, 36–45.

Xue, P., Li, Q., Xie, J., Zhao, M., and Liu, J. (2019). “Optimization of window-to-wall ratio with sunshades in China low latitude region considering daylighting and energy saving requirements.” *Applied Energy*, Elsevier, 233–234 (July 2018), 62–70.

Ye, H., Long, L., Zhang, H., and Gao, Y. (2014). “The energy saving index and the performance evaluation of thermochromic windows in passive buildings.” *Renewable Energy*, Elsevier Ltd, 66, 215–221.

Yuan, J., Nian, V., and Su, B. (2019). “Evaluation of cost-effective building retrofit strategies through soft-linking a metamodel-based Bayesian method and a life cycle cost assessment method.” *Applied Energy*, Elsevier, 253 (July), 113573.

Zhang, W., and Wang, N. (2017). “Bridge network maintenance prioritization under budget constraint.” *Structural Safety*, Elsevier Ltd, 67, 96–104.

Zheng, D., Yu, L., and Wang, L. (2019a). “Research on Large-Scale Building Energy Efficiency Retrofit Based on Energy Consumption Investigation and Energy-Saving Potential Analysis.” *Journal of Energy Engineering*, 145(6), 04019024.

Zheng, D., Yu, L., Wang, L., and Tao, J. (2019b). "A screening methodology for building multiple energy retrofit measures package considering economic and risk aspects." *Journal of Cleaner Production*, Elsevier Ltd, 208, 1587–1602.