STATE OF CALIFORNIA • DEPARTMENT OF TRANSPORTATION

TECHNICAL REPORT DOCUMENTATION PAGE

TR0003 (REV 10/98)

1. REPORT NUMBER CA21-3631	2. GOVERNMENT ASSOCIATION NUMBER	3. RECIPIENT'S CATALOG NUMBER
4. TITLE AND SUBTITLE Cross-Asset Optimization Model Development Services		5. REPORT DATE July 26, 2021 6. PERFORMING ORGANIZATION CODE IDS Infrastructure Data Solutions, Inc.
7. AUTHOR Mahmoud Halfawy		8. PERFORMING ORGANIZATION REPORT NO.
9. PERFORMING ORGANIZATION NAME AND ADDRESS IDS Infrastructure Data Solutions, Inc. 2 Research Drive, Suite 150E Regina, SK S4S 7H9 CANADA		10. WORK UNIT NUMBER 11. CONTRACT OR GRANT NUMBER 65A0755 13. TYPE OF REPORT AND PERIOD COVERED Research Executive Final Report July 2019 – July 2021
12. SPONSORING AGENCY AND ADDRESS California Department of Transportation P.O. Box 942873, MS #83 Sacramento, CA 94273-0001		14. SPONSORING AGENCY CODE Caltrans CT 65A0755

15. SUPPLEMENTARY NOTES

16. ABSTRACT

This project investigated the application of a novel cross-asset optimization methodology to help Caltrans optimize project selections and budget allocations, maximize the value of investment, and optimally achieve performance objectives by directing investments where most needed. The methodology integrates Caltrans' prior research efforts on developing project-level MODA model into a holistic cross-asset optimization framework that supports trade-off analyses and optimal development and management of programs and budgets across the entire transportation asset portfolio. The scope of this project was limited to bridges and pavements. However, the applicability of the methodology has been evaluated in the context of supporting other asset classes. To demonstrate the reasonableness of the methodology, the data and methods were validated using a software tool, called Asset Optimizer™. Comparison of the projects recommended by the proposed methodology and Caltrans' 2020 SHOPP projects demonstrated a reasonable level of agreement of project selections. The proposed methodology can potentially support programming and budgeting decisions at Caltrans, promote consistency and transparency in project selection and evaluation, and establish a quantitative and repeatable process. Future implementation of the methodology could be piloted for a number of selected districts, and benchmarked against current processes and actual project portfolios. With additional validation and testing, an implementation of the proposed cross-asset optimization methodology could provide an improved means to support decisions on performance target setting and evaluation, cross-asset budget distribution, bundling analysis, multi-year program development, and funding allocations.

17. KEY WORDS	18. DISTRIBUTION STATEMENT	
Asset management, cross-asset optimization, asset investment planning, program development, funding allocation, program management.	No restrictions. This document is available to the public through the National Technical Information Service, Springfield, Virginia 22161.	
19. SECURITY CLASSIFICATION *(of this report)* Unclassified	20. NUMBER OF PAGES 145	21. COST OF REPORT CHARGED N/A

DISCLAIMER STATEMENT

Final Report

Cross-Asset Optimization Model for Investment Planning of Transportation Infrastructure Assets

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July 26, 2021

Abstract

This project investigated the application of a novel cross-asset optimization methodology to help Caltrans optimize project selections and budget allocations, maximize the value of investment, and optimally achieve performance objectives by directing investments where most needed. The methodology integrates Caltrans' prior research efforts on developing project-level MODA model into a holistic cross-asset optimization framework that supports trade-off analyses and optimal development and management of programs and budgets across the entire transportation asset portfolio. The scope of this project was limited to bridges and pavements. However, the applicability of the methodology has been evaluated in the context of supporting other asset classes. To demonstrate the reasonableness of the methodology, the data and methods were validated using a software tool, called Asset Optimizer™. Comparison of the projects recommended by the proposed methodology and Caltrans' 2020 SHOPP projects demonstrated a reasonable level of agreement of project selections. The proposed methodology can potentially support programming and budgeting decisions at Caltrans, promote consistency and transparency in project selection and evaluation, and establish a quantitative and repeatable process. Future implementation of the methodology could be piloted for a number of selected districts, and benchmarked against current processes and actual project portfolios. With additional validation and testing, an implementation of the proposed cross-asset optimization methodology could provide an improved means to support decisions on performance target setting and evaluation, cross-asset budget distribution, bundling analysis, multi-year program development, and funding allocations.

Executive Summary

Optimization of cross-asset programming has been a long-standing problem that posed several modeling and computational challenges. Transportation asset management (TAM) programs allocate funds among competing projects to address different types of needs across all transportation assets. Projects are selected to meet a range of performance and financial constraints, and achieve organizational objectives with respect to specific performance targets.

TAM programming is inherently an integrated cross-asset and multi-objective process that requires the assimilation of a multitude of data, models, and trade-off analyses. However, current work practices have resulted in significant process fragmentation that created inefficiencies for effective cross-asset system-level analyses, mainly due to the difficulty to integrate and streamline inter-dependent data and decision models, within and across departments or functional units managing different asset classes or sub-systems. Over the past decade, Caltrans has undertaken several initiatives to study and implement cross-asset optimization models to support programming and budgeting decisions. One of the key initiatives involved the development of a multi-objective decision analysis (MODA) model to support project prioritization and selection based on monetization of project benefits with respect to organizational performance objectives. However, as a project-level trade-off analysis model, MODA was not integrated with predictive performance models, and did not support analyzing long-term impact of project portfolios.

This project aims to develop a novel cross-asset optimization methodology to help Caltrans optimize project selections and budget allocations, maximize the value of investment, and optimally achieve performance objectives by directing investments where most needed. The methodology integrates Caltrans' existing project-level MODA model into a holistic cross-asset optimization framework that supports trade-off analyses and optimal development and management of programs and budgets across the entire transportation asset portfolio. The scope of this project was limited to bridges and pavements. However, the applicability of the methodology has been evaluated in the context of supporting other asset classes.

Effective programming and budgeting decisions require the integration of project-level analysis and system-level cross-asset analysis. Based on robust optimization procedures, the proposed methodology integrated asset-level, system-level, and program-level analyses in a single framework to support efficient workflows between inter-dependent decision processes. The methodology also provided several techniques for selecting optimal treatment types and timing, performance and risk modeling, analyzing what-if scenarios, performing capital versus maintenance investment trade-off analysis, optimizing budget distribution among different asset classes, and performing bundling analysis.

Asset lifecycle models, treatment strategies, and methods to assess and forecast asset-level performance measures are developed for each asset class before considering cross-asset analysis. To optimize treatment selections, we utilized an innovative asset-generic multi-objective optimization algorithm that considers multiple objectives: minimization of risk, maximization of performance, and minimization of costs, within defined funding and performance constraints. Unlike previously developed optimization algorithms, this algorithm is characterized by its

scalability, ease of configuration and use, and its ability to converge to a global optimal solution within a reasonable timeframe.

Planning scenarios produce optimized list of annual treatments that are used to perform detailed system-level trade-off analysis across multiple asset classes, and select projects that maximize assets performance within funding constraints. Scenario analysis can accurately evaluate minimum funding needs to meet performance targets, and to assess the impact of different funding levels on performance measures. Scenarios are also used to identify optimal budget allocations, and guide project selection to accomplish performance objectives at lowest costs.

Projects nominated into any program are subsequently analyzed and ranked based on MODA program-level performance objectives. As projects progress and funds are committed and consumed, the status of projects and funds are continuously tracked and updated to allow for continuous evaluation or adjustments to the programs, and to enable timely decisions.

Implementation of the proposed methodology was supported using a software tool, called Asset Optimizer^{TM}. Asset Optimizer is a cloud-based geo-enabled cross-asset optimization and decision analytics platform that implements various components of the proposed methodology. The software implements a comprehensive data model that embodies key data elements and relationships needed to model and analyze assets data, needs, lifecycle performance, and programming and budgeting decisions. The proposed methodology can potentially support programming and budgeting decisions at Caltrans in a number of ways, such as:

- Efficient development and management of programs and budgets across the entire transportation asset portfolio.
- Identification of optimal budget allocation and balanced investment strategies to meet performance objectives and ensure long-term sustainability of assets.
- Quantify trade-offs between funding levels and performance measures for different asset classes and groups, across the entire asset portfolio.
- Implementation of common performance management, lifecycle models, trade-off analyses, and programming decision models across different districts, thus promoting consistency and transparency in project evaluations, and establishing a quantitative and repeatable process.

The proposed methodology could become as an important tool for supporting Caltrans' programming and budgeting decisions and processes. Comparison of the projects recommended by the proposed methodology and Caltrans' 2020 Strategic Highway Operations and Protection Plan (SHOPP) projects demonstrated a reasonable level of agreement of project selections. Given the differences between our modeling approach and Caltrans' current methods, we can reasonably expect that further alignment of the modeling assumptions to better reflect Caltrans' decision criteria will result in a higher degree of agreement and consistency.

Future implementation of the methodology could be piloted for a number of selected districts, and benchmarked against current processes and actual project portfolios. This application could also implement analyses to support decisions on performance target setting and evaluation, cross-asset budget distribution, bundling analysis, multi-year program development, and funding allocations, both on a district and statewide levels.

Acknowledgments

The author would like to sincerely thank the California Department of Transportation for their support of this project. The author especially acknowledges the support, guidance, and collaboration of Dawn Foster, Loren Turner, and Michael Johnson. Their insightful questions, and excellent guidance greatly helped to shape and direct this work. The author also appreciates the great work and support of Lee Hicks of the Division of Research and Innovation for coordinating and facilitating the project.

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1 Introduction

Cross-asset programming and resource allocation has been a long-standing challenge for transportation asset management (TAM). TAM programming decision-making is inherently an integrated cross-asset and multi-objective process that requires the assimilation of a multitude of data and models, involving system-level trade-offs to optimize project selections and budget allocations, while considering performance targets and risk levels across all asset classes. Current work practices have resulted in significant process fragmentation, which have created inefficiencies for implementing effective cross-asset analyses, mainly due to the difficulty to integrate and streamline inter-dependent data and decision models within and across departments or functional units managing different asset classes or sub-systems. This challenge has been exacerbated with the presence of several asset-specific isolated management systems, that created “silos” of information and decisions. Today, many of the analysis steps and processes undertaken for TAM programming and resource allocation are mostly performed in an unstructured or qualitative manner, considering a subset of the asset portfolio (e.g., specific asset classes, departments or districts), and without quantifying system-level or long-term trade-offs and implications of decisions.

TAM programs allocate, typically limited, funds among competing projects to address different types of assets’ needs across different asset classes. Selected projects should meet a range of constraints imposed by policies and strategies designed to meet organizational objectives with respect to specific performance and risk targets. With rising demands to meet higher and sustainable performance targets, combined with an ever-limited budgets, deteriorating assets, and complex regulatory requirements, there have been a broad consensus on the need to develop a new cross-asset optimization methodology that can potentially “bridge the gaps” through providing a holistic decision-making framework that enables the integration of TAM programming processes.

Over the past years, Caltrans has undertaken several initiatives to optimize strategies and programs for preserving and improving its vast transportation network. In fact, the application of cross-asset optimization for program development has been an active research at Caltrans since 2012 [1]. This project falls under Caltrans’ business strategy to enhance TAM programming and budgeting decisions on a statewide and district levels.

In an abstract form, the asset investment planning (AIP) and cross-asset optimization model can be viewed as a process that maps four inputs to two outputs (Figure 1). This process utilizes information on asset classes inventories and sets of identified needs, and apply constraints on funding levels and performance targets, to produce sets of optimized cross-asset multi-year programs, which in turn will be summarized and communicated in a number of plans and reports (e.g., TAMP, STIP). This mapping process is achieved through a series of analyses iterations until programs and performance measures are optimized and balanced to meet desired targets within funding constraints.

This project proposes a novel cross-asset optimization methodology to help Caltrans optimize programming and budgeting processes across the entire transportation asset portfolio. The methodology integrates with Caltrans' project-level multi-objective decision analysis (MODA) model, and enables system-level cross-asset analysis to support:

- Efficient development and management of capital and maintenance programs across the entire highway system asset portfolio; and
- Identification of optimal budget allocation and balanced investment strategies across different asset classes to meet performance objectives and ensure long-term sustainability of infrastructure assets.

The methodology provides a set of techniques to select projects that maximize assets performance within funding constraints; identify optimal and balanced budget allocations to accomplish performance objectives at lowest costs; quantify trade-offs between funding levels and performance measures; and accurately evaluate funding needs and the impact of different investment strategies on performance measures. The proposed methodology is supported by a software tool, called Asset Optimizer. The scope of this project was limited to two classes of transportation assets: pavements and bridges. However, the applicability of the proposed methodology has been evaluated in the context of supporting other asset classes.

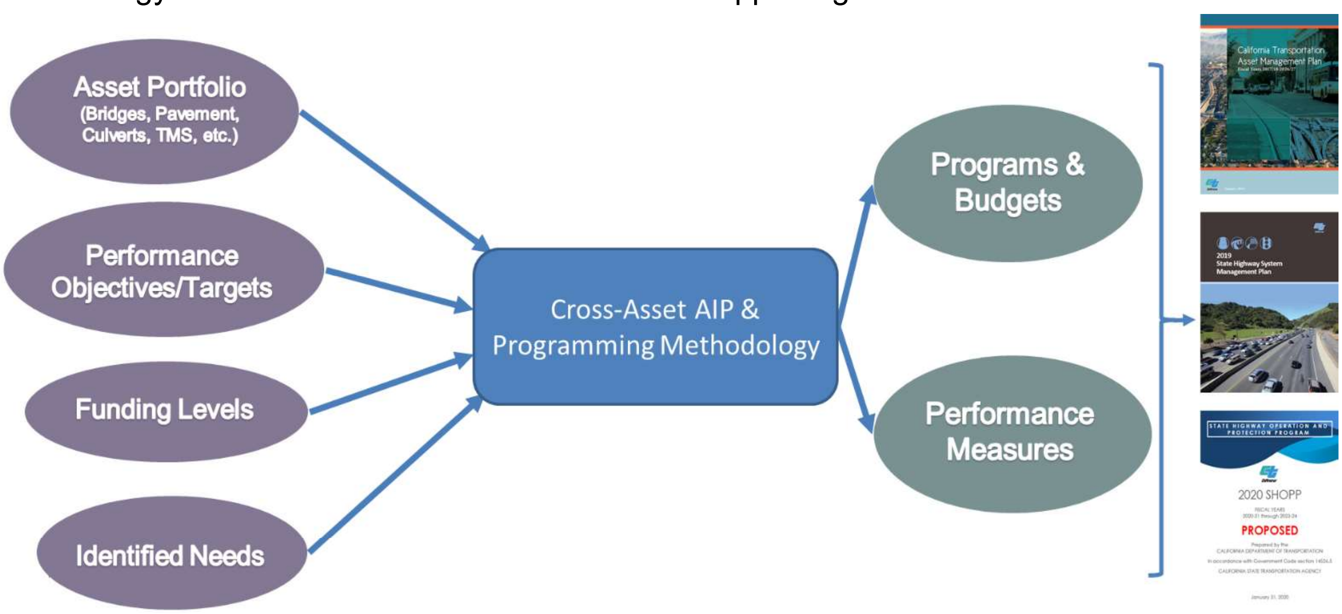


Figure 1: An abstract input-output view of the TAM programming process

2 Background

Over the past decade, Caltrans has undertaken several initiatives to study and implement cross-asset optimization for program development. In 2012, CTC & Associates LLC performed a study on behalf of Caltrans' Division of Research and Innovation (DRI) to investigate the application of cross-asset optimization in transportation asset management [1]. The study reviewed the state-of-practice and related research, and concluded that no state DOT, at that time, has completed an implementation of cross-asset optimization within and across all asset categories at both the system and project levels. The study concluded that state DOTs' practices appeared to prioritize projects based on ranking criteria defined by a utility function, and *no applications of optimization methods were reported*.

In 2014, Caltrans initiated a pilot project to develop a new multi-objective decision analysis (MODA) model to assess projects benefits (or values) and to prioritize the Strategic Highway Operations and Protection Plan (SHOPP) projects based on value-to-cost ratios. The MODA model and associated Excel-based tool were tested using the existing 2014 and 2016 project portfolios. However, a number of limitations of the new model were observed and a number of improvements were recommended [2, 3].

Other notable efforts to solve the cross-asset optimization problem include the work undertaken by Cambridge Systematics Inc on behalf of the New Jersey DOT's (NJDOT) Office of Capital Investment Strategies (CIS) to develop a decision support model to optimize budget allocation decisions [4]. The study reviewed current practices in Florida, Georgia, Michigan, Ohio, and Utah DOTs and concluded that projects are often prioritized using scoring approaches with greater reliance on manual processes, where asset management systems are used to predict performance given a budget scenario. The study also proposed a utility function to aid NJDOT to prioritize projects with the objective to maximizing utility.

The FHWA's Transportation Asset Management Expert Task Group (TAM ETG) published a discussion paper [5] that emphasized the need to address cross-asset trade-offs and optimization, as the next generation of innovation to improve decision-making in transportation agencies. The TAM ETG defined cross asset optimization as "*the use of recursive mathematical computations to determine the maximum utility for a given set of investments constrained by defined performance parameters.*" The discussion paper emphasized that the use of an optimization approach would produce more sophisticated and quantified results but require extensive asset and project data.

The NCHRP Report 806 [6] proposed a model and developed Excel-based prototype to demonstrate the feasibility of a cross-asset budget allocation approach to support performance-based project prioritization, and program development. Although the study emphasized the importance of optimization models for developing cross-asset programs, it also highlighted the associated challenges for testing all combinations of assets and alternative improvement actions, which would be infeasible to enumerate and search using traditional brute-force search methods.

Thompson et al. [7] extended the models developed in the NCHRP Report 806 and proposed a cross-asset performance-based framework to support trade-off analysis and asset management planning. The framework considered both asset-specific and asset-generic models for TAM planning, and provided a methodology for setting and tracking performance targets. The report proposed the development of an Excel-based asset-generic trade-off analysis tool that consumes data from existing bridge and pavement management systems.

Focusing on TAMS financial planning aspects, the NCHRP Report 898 [8] proposed a 10-step methodology to support the development of investment strategies. The methodology starts by defining investment scenarios and forecasting future asset performance based on the defined scenarios. The methodology then identifies project candidates based on initial budget allocation, and subsequently selecting projects for each scenario and then finalizing budgets. The study noted that projects should be selected to maximize benefits while minimizing lifecycle costs, subject to budget constraints. However, the study acknowledged that "*determining a mathematical optimum may be difficult or impossible unless the selection is performed within more narrowly defined categories*," and therefore the study proposed using the MODA approach if the budget is set for "fewer" or "broadly defined" asset/investment categories.

3 Overview of the Proposed Cross-Asset Optimization Methodology

Lessons learned from previous work highlighted the challenges and the need for integrating asset-level, system-level, and program-level analyses in the same framework. Combining these multiple types of analyses in a single framework is critical to support efficient information flow and decisions, which are typically inter-dependent. These trade-off analyses inform and guide decisions with respect to performance target setting, project selection and prioritization, multi-year program development, and budget allocation. Justification of decisions and communication with stakeholders also require close integration among these different levels of analysis. However, none of the previous work we reviewed seemed to offer a framework that can integrate these multiple levels of analyses. Our proposed methodology is an attempt to accomplish this goal.

Figure 2 depicts the typical flow of information across the three levels of analyses. A brief description of each level is provided below.

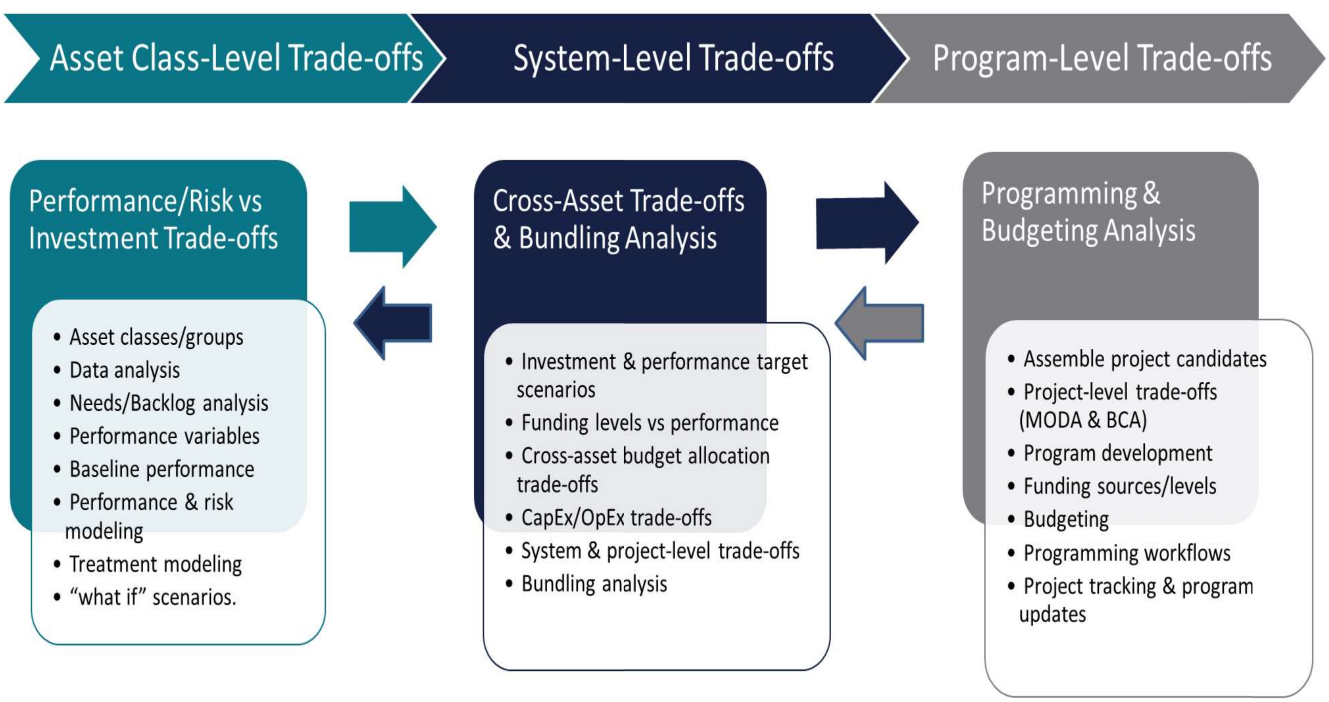


Figure 2: Different levels of trade-off analysis in the proposed methodology

3.1 Asset Class-Level Analysis

TAM programming requires analyzing a portfolio of dissimilar assets with unique lifecycle, performance, and risk parameters to find the best trade-offs and optimal project mix. This analysis is performed on each individual asset class (bridges, pavement, culverts, TMS, etc.), considering assets unique lifecycle models, performance objectives, treatment strategies, and investment scenarios. This step involves the development of optimal multi-year lists of treatments for individual asset classes under a range of scenarios using the multi-objective optimization algorithm.

3.2 Cross-Asset System-Level Analysis

Programming decisions always involve balancing competing objectives (cost, performance, risk, etc.), and therefore performing trade-off analysis is required to inform and guide decisions at multiple levels. System-level trade-off analysis is then performed using the results from asset class-specific scenarios, and considering system-level performance measures to identify ideal budget allocation and select the scenarios that maximize overall portfolio performance. This analysis also evaluates trade-offs between funding levels and performance measures, trade-offs between capital and maintenance funding levels, and trade-offs between investment distribution among different asset classes (e.g., bridges versus pavement investment levels).

System-level trade-off analysis establish a quantitative relationship between investment levels and distributions versus performance measures, which will guide decisions on balancing investments across different programs and asset classes. In addition, this analysis would identify opportunities for bundling treatments into practical projects to reduce costs and risks, improve coordination, and increase project delivery efficiencies.

3.3 Program-Level Analysis and Decision-Making

Program-level analysis involves using the set of optimized treatment candidates produced by the previous levels of analyses to support the assembly and evaluation of project portfolios, and guide decisions on project selections and prioritization, as well as program and budget development. The set of candidate projects are evaluated using techniques such as multi-objective decision analysis (MODA) and lifecycle benefit-cost analysis (BCA). Project evaluations typically utilize organizational performance measures that are common to all asset classes (e.g., safety, mobility, environmental sustainability).

Figure 3 shows a schematic of the proposed methodology, depicting the organization, inter-relationships, and information flow of the key processes that are typically undertaken within TAM programming. It is worth noting that the arrows in this diagram mainly depict information flow among different processes, and do not necessarily reflect a sequential order of execution. In fact, at any point in time, many of these processes may be running concurrently to support different levels of analyses and decision-making. The remaining sections in this report provide more details on these processes.

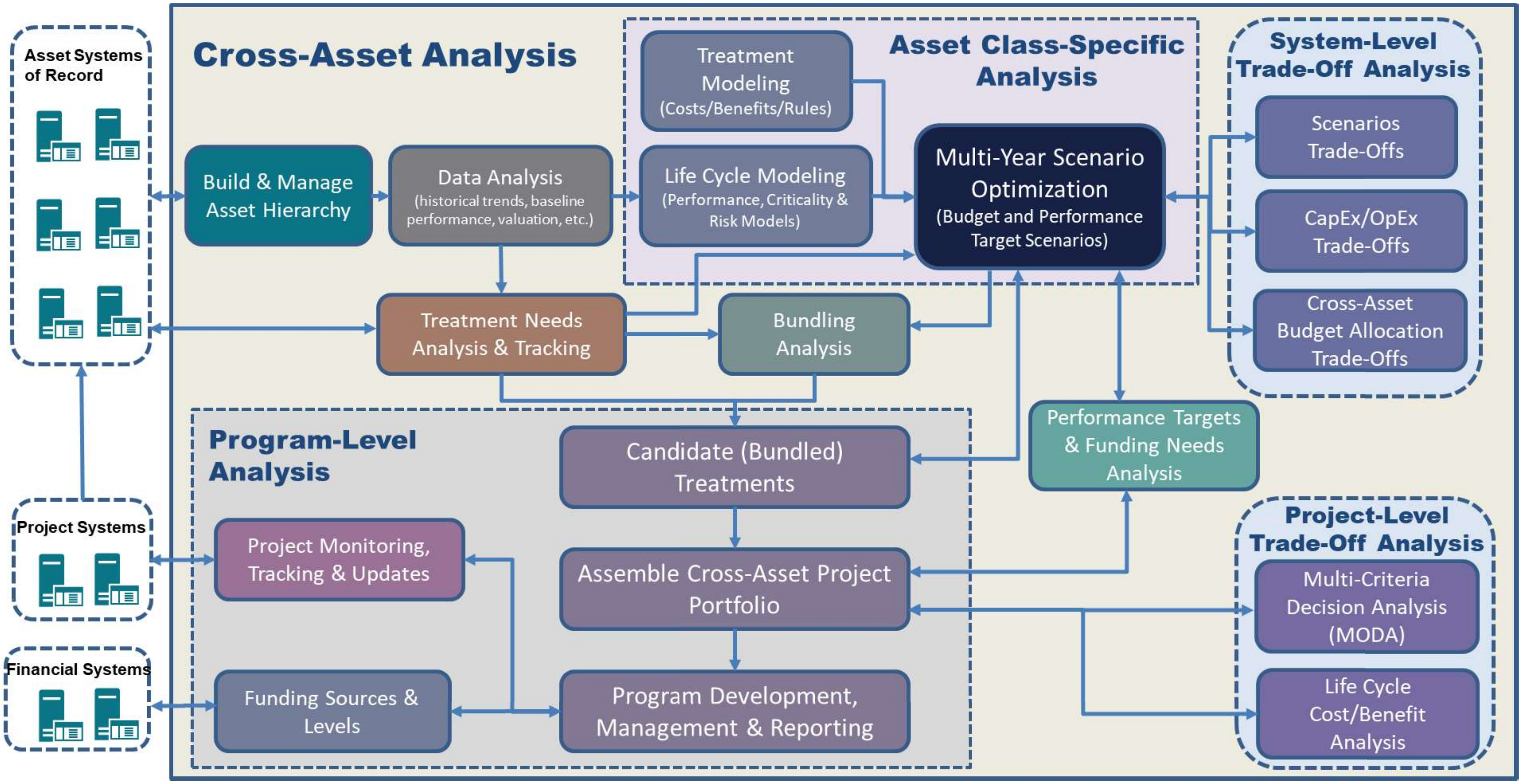


Figure 3: Schematic of the main processes and information flow in the proposed methodology

4 Overview of the Information Model

Efficient implementation of the proposed methodology requires the use of an integrated and comprehensive data model that embodies key data elements and relationships needed to model and analyze assets data, lifecycle performance, and programming and budgeting decisions. This data model should satisfy the information requirements of each process depicted in Figure 3, and should define common and consistent semantics to ensure data integrity and consistency across various processes.

Figure 4 shows a high-level conceptual Entity Relationship Diagram (ERD) of the data model, highlighting the key entities and relationships. This diagram uses crow's foot notation to describe the relationships between entities. A brief description of some of the key entities is provided in Table 1.

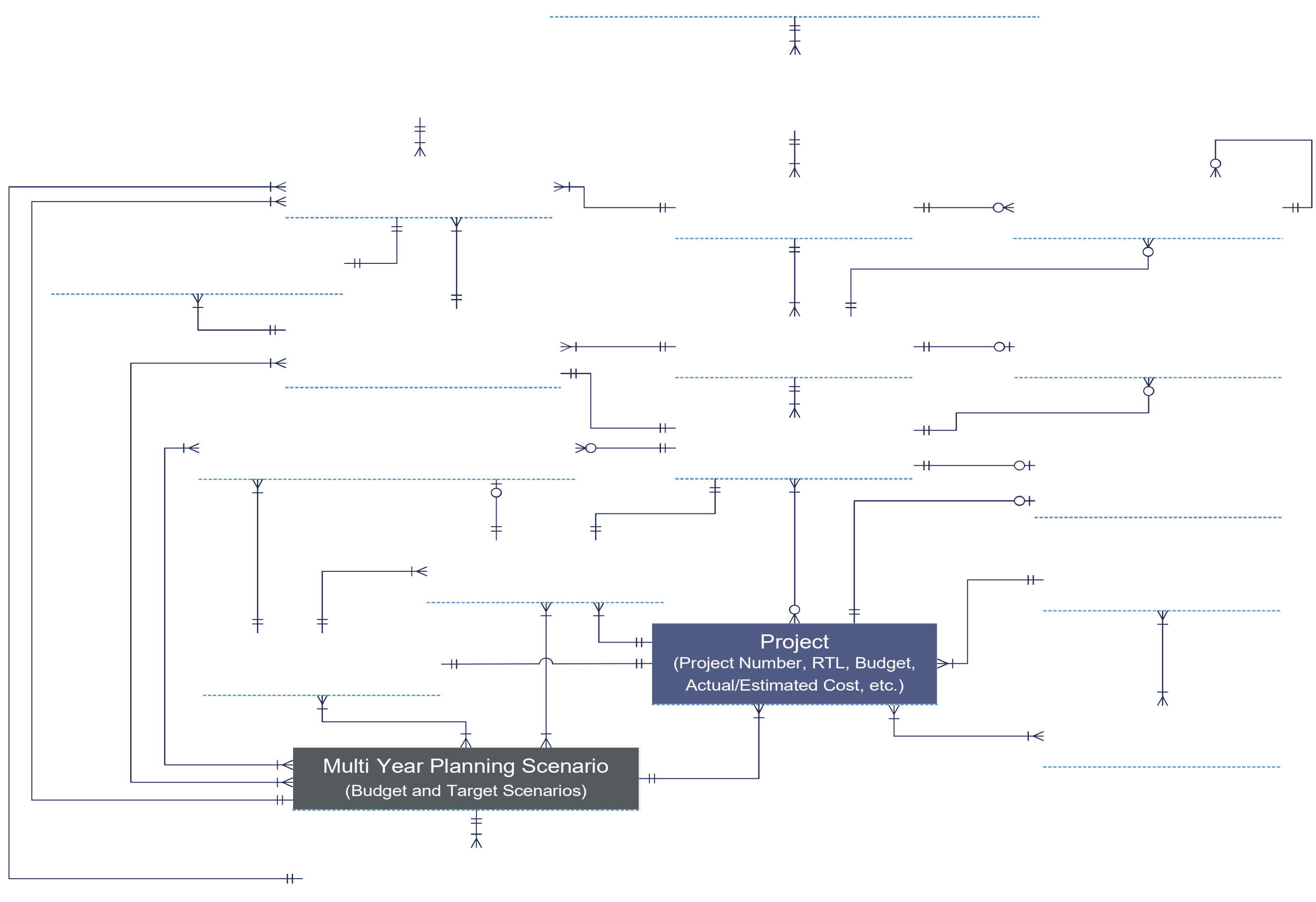


Figure 4: High-level conceptual Entity Relationship Diagram (ERD) of the proposed data model

Table 1. Description of Some Key Entities in the Proposed Data Model

Entity	Description
Treatment	Treatment represents one or more action (i.e., work type) such as rehabilitation, repair, replacement, or functional improvement actions (e.g., deck overlay, bridge replacement, HMA thin overlay, etc.). These actions are applied to a specific asset, and has associated time and estimated cost. Treatment models are asset-type specific and used to optimize project selections in a given planning scenario. Treatment models include: cost model, benefit (or effectiveness) model, and a set of applicability (or feasibility) constraints that describe the rules or strategies for applying a specific treatment type. Treatments can be recommended based on NEEDs, optimization of planning scenarios, or based on other criteria (e.g., performance objectives).
Treatment Bundles	A collection of treatments applied to different assets, which may be of the same or different asset types. Bundles are identified based on spatial and temporal analysis and can be used to coordinate/align projects to increase efficiencies. Treatment bundles can be used to define project candidates for a specific program.
Project	A project can include one treatment or a bundle of treatments applied to one or more assets, possibly of different types (e.g., bridge and pavement treatments). Key project attributes include date, cost, estimated cost, advertisement date, status, etc.
Program	A program is a collection of projects that are planned and delivered over multiple years following specific guidelines (e.g., meeting specific organizational goals, funded through specific sources, time horizon, etc.). Programs are initially assembled from a collection of candidate projects that are subsequently planned, programmed, and delivered following pre-defined workflow processes.
Proposed Work (or NEED)	NEEDs represent proposed treatments identified based on asset deficiencies or performance requirements. Part of NEEDs identification also involves identifying the recommended treatment (or work type), time frame, and estimated cost. NEEDs can be bundled and used to recommend projects.
Multi-Year Planning Scenario	Investment planning scenarios are used to evaluate the impact of various funding levels on assets performance and risk measures, and to evaluate funding requirements to achieve performance targets. Optimization is used to automatically identify treatments that will maximize assets performance, minimize risk, at the lowest costs. For each asset, a scenario defines an optimal plan for maintaining the asset over the planning horizon, including all treatments, times, costs, and predicted values of performance measures.

Entity	Description
Assets Portfolio	This entity represents the highest level in the asset hierarchy, which includes all asset types and assets organized in a tree-like structure. A typical asset hierarchy arranges the asset portfolio into different asset systems, classes (or types), and sub-classes. An example asset portfolio includes asset systems such as bridges, pavement, TMS, culverts, etc. Any number of levels of sub-classes may be defined to organize specific groups of assets (e.g., based on districts, functional classification, etc.). An asset class includes the asset inventory, along with any related data (e.g., inspection, condition, etc.).
Asset System	Asset systems are collections of Asset Classes of a specific type of assets. For example, the pavement asset system may include asset classes such as Class I, Class II, and Class III Pavement Segments, whereas a bridge asset system may include interstate bridges and non-interstate bridges as separate asset classes.
Asset Class	An asset class represents a collection of assets of one or more types that will be used to define consistent sets of performance metrics, treatment strategies, lifecycle models, and planning scenarios. An asset class is often defined for one asset type (e.g., bridges or pavement. However, a class may also include assets of different types.
Asset Sub-Class	Asset sub-class is another level of assets grouping to organize assets within a class based on some key asset attributes. Examples of asset sub-classes may group bridges or pavement under the bridge or pavement classes based on owner (State, Local, etc.), District, or Functional Classification (e.g., Interstate, NHS).
Asset Inventory	Asset Inventory is a collection of records for assets that belong to a specific asset class. Examples of asset inventories include bridge NBI data, or pavement HPMS tables. Asset records can include any set of asset attributes, depending on the type of asset. Asset Inventory may include "historical" data of the asset class records. For example, the asset inventory of bridges may include historical NBI inventory records.
Asset Group	Asset groups are collections of assets that are assumed to have somewhat "homogeneous" characteristics in terms of their deterioration rate and/or criticality (or expected consequence of failure). Asset groups are used to define a consistent set of lifecycle models to predict asset performance and criticality, and therefore, are expected to exhibit enough similarity to allow the development of these models at an appropriate level of graduality. For example, a bridge inventory may be subdivided into different asset groups based on functional classification, bridge material, structural system, etc. (e.g., interstate concrete box girder continuous span bridges, non-interstate prestressed girder bridges, etc.). It is important to define asset groups at an appropriate level of granularity to balance the level of desired accuracy in predicting performance and criticality, with the time and effort needed to build asset group-specific models.

Entity	Description
Asset	Asset is the basic physical entity in the transportation infrastructure system, which is managed and preserved throughout its life cycle. Examples of assets include a bridge, pavement segment, or culvert. Asset records populate an asset inventory, which belongs to a specific asset class. A typical transportation system includes many different types of assets; each has unique physical, operational, and risk characteristics, and require specific treatment methods and management strategies.
Cross-Asset Analysis	Analysis that considers a portfolio of assets from different classes for purposes of: (1) optimize budget allocations to balance investment strategies across multiple asset classes and direct investments where needed; and (2) optimize project selection and bundling to improve program development and delivery. Unlike system (or network)-level analysis that considers assets and treatments in the same asset class (e.g., pavement or bridge assets), cross-asset analysis aims to maximize performance of the entire asset portfolio and increase efficiencies/benefits of projects involving multiple asset classes. This research project proposes a set of tools for cross-asset analysis to support life cycle planning and program development process.
Performance Measure	Performance measures are a set of asset attributes that are used to record, analyze, predict, and report asset performance metrics. Examples of these measures include deck, superstructure, or substructure condition of a bridge, or the distress parameters (IRI, rutting, cracking, or faulting) of a pavement segment. These measures are often time-dependent attributes, unlike static asset attributes such as location, material construction year, etc. Other time-dependent variables may include traffic volume or scour. Because of the "dynamic" nature, each performance measure is associated with a predictive model to forecast its value at any point in the future. Performance measures can have inter-dependencies and as such be defined using a hierarchical structure (e.g., bridge condition can be derived from the condition of deck, superstructure, and substructure). Similarly, the condition of a pavement segment can be calculated based on IRI, rutting, and cracking indices. Asset condition, criticality, and risk are calculated and predicted based on one or more performance measures. While condition-related measures represent the structural adequacy of assets, criticality measures represent such parameters as essentiality to the public, functional classification, or other socio-environmental-economic factors. Performance measures are often impacted (or improved/reset) by treatments. For example, the roughness of a pavement segment will be reduced or reset as a result of an overlay. These improvements are defined as part of the treatment benefits/effectiveness models.

Entity	Description
Performance Target	Performance targets are defined for a selected set of performance measures to reflect desired or mandated performance levels to achieve over the planning horizon. Defined targets are used to assess performance gaps or funding needs required to meet performance requirements. Analysis of planning scenarios would show the impact of various investment levels on meeting performance targets. It can also help refine asset management strategies and determine required funding levels to optimally meet performance targets now and into the future.
Predictive Model	Predictive models are asset group-specific statistical models defined to help forecast an asset's future performance and risk metrics at any point in time. Deterioration models are specific types of predictive models used specifically to forecast assets condition attributes. Other predictive models may be used to predict such parameters as traffic volume, scour growth, etc. Predictive models of performance measures are defined for each asset group. For example, the deterioration model of a bridge deck may be different depending on the bridge structure type or function. However, for some models (e.g., traffic volume growth) may be used in different asset groups.
Treatment Cost / Benefit Model	For each treatment, users define cost models to estimate treatment cost based on any number of variables (e.g., unit cost, asset attributes such as area or length, condition state). Benefits are defined in terms of "condition improvement increments", which represents the treatment's effectiveness for extending the asset's service life or reducing risk of failure. Examples of improvements include higher condition ratings for bridge deck, superstructure, or substructure.
Treatment Rules / Constraints	A set of constraints are defined for each treatment to ensure the feasibility and cost-effectiveness of different treatments and reflect the specific organization's preferences, previous experience, and work practices. Some constraints may limit treatment application under some circumstances, such as certain types of asset material or based on the asset condition. Some rules may also eliminate future application of specific treatments depending on prior treatments received over the planning horizon. For example, a rule may eliminate prevent the use of repair on a deck for 10 years after it receives an overlay treatment. Another rule may specify the maximum number of occurrences of a treatment (e.g., deck repair should only be applied for two times on the same deck over the planning horizon, after which another treatment should be used).
Funding Source	A source of funding used to allocate budget to programs and projects over the years. Funding is allocated to various programs and projects. Budgets can also be allocated, de-allocated, or rolled-over.

5 Lifecycle Modeling of Individual Asset Classes

Asset lifecycle models, treatment strategies, and methods to assess and forecast asset-level performance measures vary widely between different asset classes. Therefore, these models are developed separately for each asset class before considering any cross-asset analysis. This section describes some common principles of lifecycle modeling of individual asset classes. Within the scope of this project, two primary asset classes were considered: pavements and bridges. Details of the modeling and scenario analysis of Caltrans bridge and pavement state highway system (SHS) inventory are provided in Appendices A and B, respectively. However, the same principles can be applied to other asset classes.

5.1 Assets and Models Hierarchy

Asset data and lifecycle models are organized in a flexible tree-like hierarchical structure that organizes data into asset systems, classes, and groups (Figure 5). The hierarchy maintains all cross references between inventories, assets, performance measures, needs, projects, programs, and funding sources.

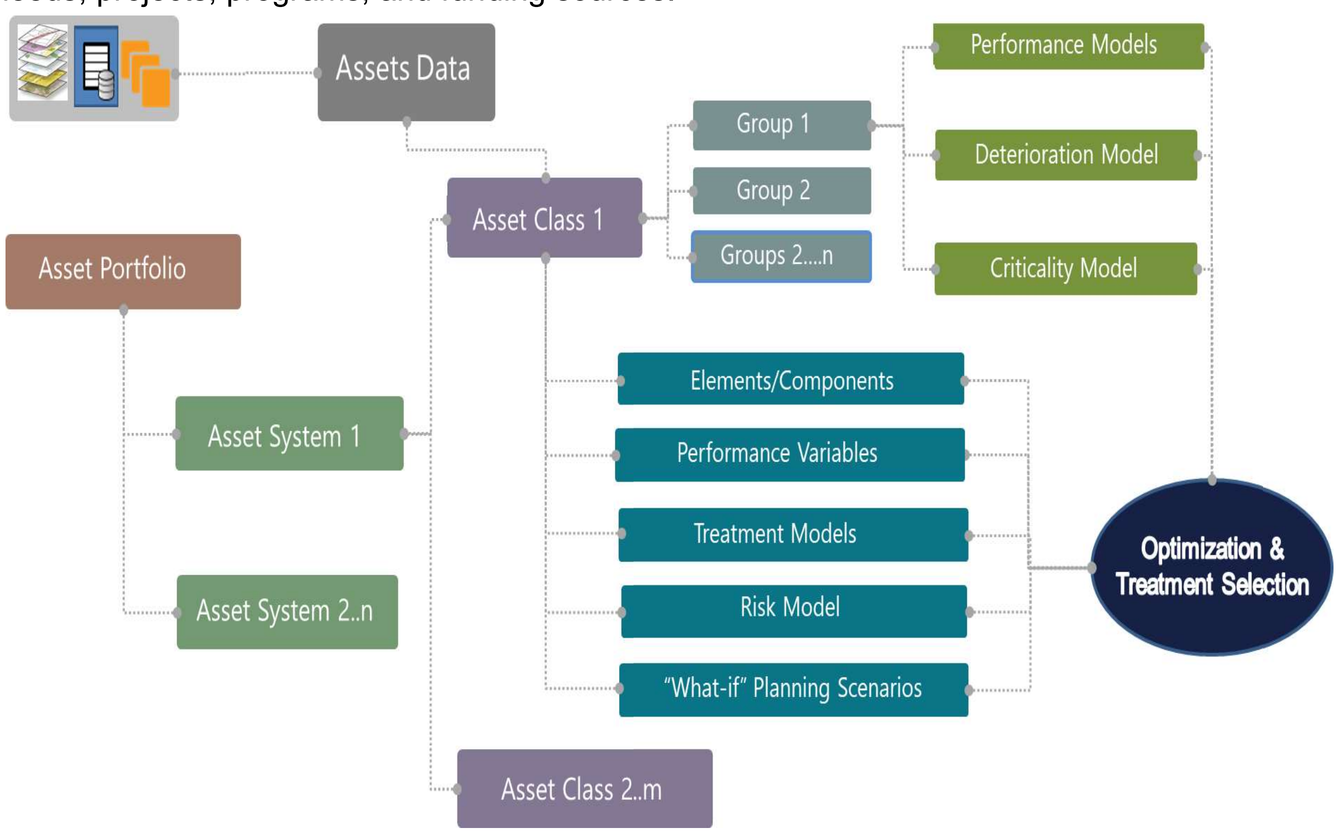


Figure 5: Organization of Assets and Models into a Hierarchy

For a typical TAM asset portfolio, asset systems may include different asset types (e.g., bridges, pavement, culverts, TMS, facilities) or assets in different organizational units (e.g., districts, local agencies). Asset systems, classes, and groups are defined based on modeling requirements, performance objectives, and funding allocation rules. Assets may be organized based on asset types, functional classification, or organizational units. Asset systems are considered containers of asset classes. Based on modeling and planning requirements, asset classes may be defined to include the same or different asset types. For example, one asset class may include all bridges or all pavements, whereas another class may include different types of Traffic Management Systems (TMS) assets (signs, signals, lighting, etc.). Different classes may also be defined for different sets of the same asset types. For example, different asset classes may be defined for interstate and non-interstate bridges.

Assets in the same asset class share a common set of performance variables, treatment models, and a risk model. Treatment models that define costs, benefits, and rules for applying different treatment actions. “What if” planning scenarios are defined and optimized for each separate asset class. Scenarios may define a specific funding profile over the planning horizon to assess the impact of funding levels on system-level condition and risk levels. Scenarios may also be defined to evaluate budget requirements to achieve certain system-level risk or condition levels. For each scenario, treatment lists are generated on an annual-basis to satisfy all defined constraints.

Asset groups can be defined for different subsets (or cohorts) of assets in the same class, based on physical or operational attributes, functional classification, deterioration and risk characteristics, geographic areas, or funding programs. Asset groups are assumed to have general characteristics in terms of their deterioration rate and/or criticality (e.g., design and construction type, material, functional class, etc.). Performance and criticality predictive models are defined separately for each group, taking into consideration specific data and modeling requirements.

5.2 Performance and Risk Predictive Modeling

Development of performance-based TAM programs relies on the assessment, forecasting and trade-off analysis of several asset-level performance measures, which requires the use of robust and reliable predictive models. Different asset classes have unique characteristics, performance measures, and risk factors. Different asset classes also have different levels of data availability, which often determine possible modeling methods and planning requirements. For example, while extensive data sets are typically available for bridge and pavement assets over multiple years, limited data sets are often available for some asset classes such as culverts and TMS. While available data would allow the development of fairly detailed predictive models in the first case, data limitations will require the use of simpler age-based data models in the latter.

Performance measures are a set of, possibly inter-dependent, asset attributes to record, analyze, predict, and report asset performance and risk metrics. Examples of these measures include the deck, superstructure, or substructure condition of a bridge, or distress parameters (IRI, rutting, cracking, faulting) of a pavement segment. Performance measures are used to describe asset-specific attributes such as its condition state, extent of distresses, capacity, or functional adequacy (e.g., bridge horizontal or vertical clearance, or lane width with respect to traffic volume). They may also be used to describe asset-level risk factors such as vulnerability or resilience (e.g., seismic or scour criticality).

The methodology utilizes a risk index metric to optimize selection of treatment type and timing to minimize risk at the lowest lifecycle costs. The risk index reflects asset condition (e.g., the structural adequacy of assets or the likelihood of asset failure) and criticality (e.g., consequence of failure, considering such factors as essentiality to the public, functional classification, or other socio-environmental-economic parameters). In this context, these asset-level risk factors which are considered as measures of performance, should be distinguished from other agency-wide systemic risks that are not asset or site-specific, such as uncertainty of future funding, regulatory requirements, or political and market factors [10]. These systemic risks are typically evaluated separately in a risk management plan, and not directly linked to the proposed methodology.

To accommodate the requirements of different asset classes with respect to different condition, capacity, or criticality factors, the proposed methodology allows the definition of a hierarchy of performance measures along with any dependencies, thus allowing for the modeling of diverse asset classes consistently within the same framework. Appendices A and B provide examples for modeling bridge and pavement performance measures, using relatively detailed models. However, more, or less, sophisticated models, or any agency-specific models could also be used instead.

Performance measures are calculated for each individual asset, and then aggregated and rolled up to system level using appropriate asset weightings. For example, the condition index of each bridge can be calculated and rolled up to a system-level average condition index based on a weighting factor (e.g., bridge deck area) reflecting the contribution of each individual asset to the system-level measure. Performance measures may also be aggregated and rolled up based on any assets grouping criteria (e.g., interstate versus non-interstate assets, different districts or local agencies) or to satisfy reporting requirements. For example, the condition state of bridges and pavement segments can be used to calculate the %Good and %Poor, for reporting the federal Transportation Performance Management (TPM) measures.

Some performance measures may be associated with specific targets to reflect the state-of-good-repair for a particular asset class. Achieving desired performance targets typically guides project selection, programming and investment decisions. “What-if” scenarios can be used to set feasible performance targets, investigate the impact of alternative investment decisions on these targets, and to determine funding requirements that achieve and sustain the targets over defined planning horizon.

Each time-dependent performance measure requires the definition of a predictive model to forecast its future value at any point in time. Predictive models can be based on a variety of statistical distributions (Weibull, exponential, polynomial, etc.), and may be univariate or multivariate models, depending on the available data and sophistication of the modeling approach. In this project, we employed several techniques to develop performance models for bridges and pavements, as described in Appendices A and B.

5.3 Modeling of Treatments Costs, Benefits, and Applicability Rules

Treatment types and timing have a significant impact on assets performance, risks, and funding needs. Treatments include all possible interventions that can be applied to address assets deficiencies through their lifecycle, including preservation, major or minor rehabilitation, functional improvement (e.g., widening), risk mitigation (e.g., seismic and scour mitigation), and partial or full replacement actions. Treatments are typically selected to address specific deficiencies or improve specific performance measures, at a specific time (Figure 6). The proposed methodology provides a flexible scheme to define different types of treatments with sets of customizable rules and formulae to reflect specific agency's preferences, experience, and work practices.

Treatment cost models are defined based on parameters such as unit costs, asset attributes, and condition state. Benefits models represent expected incremental improvements (or resets) resulting from specific treatments including condition or capacity improvements, risk mitigation/reduction, and extending assets service life.

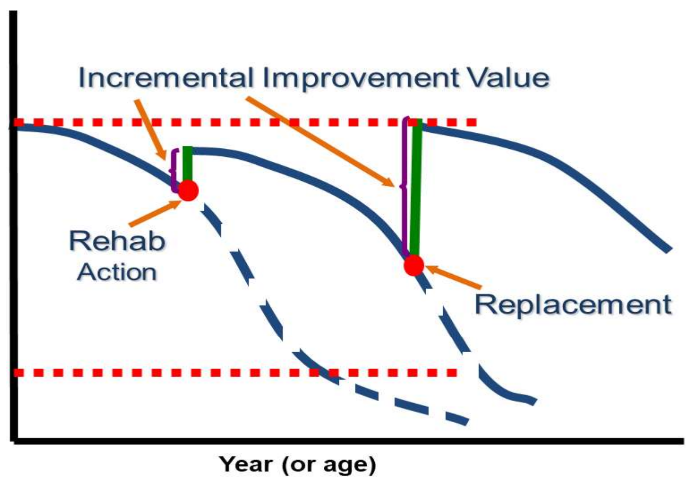


Figure 6: Treatments Impact on Assets Performance Measures

Treatment constraints define triggers and technical and economic feasibility of applying a treatment. Constraints are defined to limit the application of a treatment under certain circumstances. For example, a particular treatment may only be applicable to certain types of material or within a defined range of condition ratings. In addition, constraints may also be used eliminate future application of specific treatments depending on prior treatments received over the planning timeframe. For example, a rule may eliminate the use of repair on a deck for 10 years after it receives an overlay treatment. Another rule may specify the maximum number of occurrences of a particular action (e.g., deck repair should only be applied for two times on the same deck over the planning horizon, after which an overlay or deck replacement should be used). Constraints can also be defined to limit total expenditure or total amount of treatments in a particular work program (e.g., limiting expenditure on bridge replacement to 60% of the total budget).

Treatments models are subsequently used to optimize the selection of treatments with the best cost-benefit trade-offs. Optimal treatment timing is determined by the optimization approach described in the next section. Treatments should be applied at the right time to extend assets life and avoid more costly treatments (e.g., replacements) and reduce the risks associated with treatment deferral. For example, delaying preservation treatments will cause assets to further deteriorate to a point where costly actions will be required.

6 Asset-Generic System-Level Multi-Objective Optimization Technique

At the heart of the proposed methodology is a unique asset-generic multi-objective optimization technique[1] that optimizes system-level performance and risk-based multi-year asset management plans, while considering multiple objectives: minimization of risk, maximization of performance improvement, and minimization of lifecycle costs, subject to defined funding and performance constraints. This optimization technique is used to optimize treatment selections and scenarios for all asset classes.

Over the past decade, there have been several efforts to develop optimization models to support TAM planning. A number of these efforts employed mathematical programming methods (e.g., linear programming, dynamic programming, goal programming). Most notable is the multi-objective optimization model developed in the NCHRP Project 12-67 [10], which formulated the network-level optimization problem as a multi-dimensional knapsack problem, and proposed a solution based on the incremental utility-cost (IUC) heuristic. Other notable work involved the use of multi-attribute utility functions [11], integer and dynamic programming [12], and genetic algorithms [13, 14, 15, 16].

However, most of the proposed optimization techniques have been applied to relatively small networks and have not been tested on large asset portfolios or under a practical set of objectives and constraints. In some cases, the application of these optimization techniques requires extensive user input to assign and adjust criteria and weights, and to elicit expert knowledge on proper model parameters.

Solving this combinatorial NP-hard multi-objective optimization problem on a system-level has been a long-standing challenge. The primary reason for this complexity arises from the enormous size and combinatorial nature of the underlying search space in practical TAM planning scenarios, which typically involve thousands of assets and numerous alternative treatments, which would be virtually impossible to explore using

[1] This innovative multi-objective optimization technique was recognized by the ASCE Innovation Award in 2016.

brute-force search methods to enumerate and examine all feasible combinations, within a reasonable time frame.

This challenge was highlighted by several researchers and practitioners. For example, Patidar et al. [5] indicated that "*very large problems involving tens of thousands of bridges and numerous alternatives to be considered over a long planning horizon are not tractable*." Maggiore et al. [6] also indicated that "*testing all combinations of projects and alternatives would be infeasible.*" More recently, Spy Pond Partners et al. [8] noted that "*determining a mathematical optimum may be difficult or impossible unless the selection is performed within more narrowly defined categories.*" Thompson et al. [7] also suggested that due to the complexity of optimization tools, "*only relatively sophisticated users of these tools expect to be able to interact with parts of the models and modify them to explore scenarios or to adapt the model.*"

IDS has developed an innovative algorithm that is capable of "intelligently" searching a potentially very large search space, while ensuring scalability and robustness under different circumstances to converge to an optimal solution within a reasonable timeframe [17]. The algorithm has been implemented in a practical and user-friendly software tool that does not require users to manually configure the optimization parameters, while allowing the users to focus on analyzing scenarios and trade-offs and be able to easily modify and adapt the models by defining a limited number of parameters.

The proposed optimization technique employed a dynamic programming-based genetic algorithm. The algorithm has the following four features:

1. **Convergence to a Global Optimal Solution.** Ability to converge to a global optimal solution at the lowest computational cost, irrespective of the size of the asset inventory or number of treatment options.
2. **Scalability and High-Performance.** The algorithm takes advantage of multi-core high-performance computing by executing processes in parallel. To ensure scalability and efficient operation for any problem size (i.e., size of the asset inventory or number of treatments), the algorithm can adaptively adjust its parameters to ensure fastest convergence to an optimum solution.
3. **Asset-Generic.** The algorithm is applicable to any asset class and follows a consistent process for assets lifecycle modeling and can adapt to varying levels of data availability.
4. **Easy Configuration.** Configuration of the models and scenario parameters (funding levels, performance targets, etc.) can be easily done without the need for any model formulation or scripting.

Planning scenarios can represent a range of funding levels, desired performance targets, and treatment strategies/rules. Each scenario will produce a pareto-optimal list of annual treatments that optimize assets lifecycle performance, risk, and costs over the planning horizon, subject to performance and funding constraints. The scenarios are used to investigate the impact of different funding levels, treatment strategies, or currently committed projects on performance measures. Scenarios can also be used to evaluate funding requirements to meet identified needs or to achieve performance and risk targets. Figure 7 shows a flowchart of the scenario optimization approach.

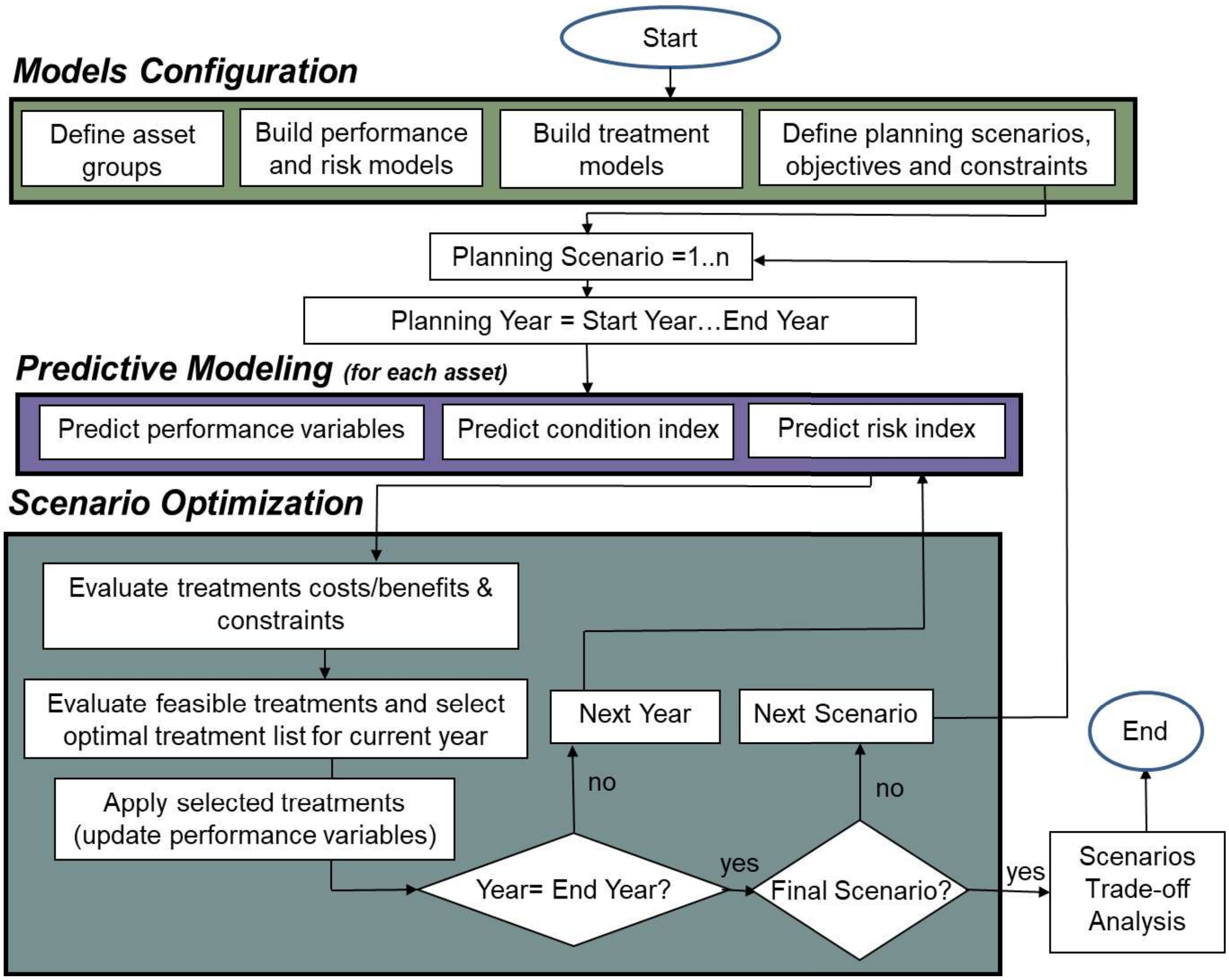


Figure 7: Flowchart of the optimization approach used in “what if” scenario analysis

For each of the defined scenarios, the algorithm proceeds sequentially from year to year. At the beginning of each year, performance measures are predicted for each asset using defined predictive models and taking into consideration any treatments that have been planned in previous years. Assets’ criticality, which reflects the possibility of structural or functional inadequacy of a given asset, is determined by evaluating a set of rules and user-defined weights that involve static or time-dependent risk factors (e.g., functional class, traffic volume, detour length, etc.).

For each asset, feasible treatments are then identified based on the defined applicability constraints. The cost and impact of each treatment are then evaluated. The multi-objective optimization model stochastically searches all possible treatment trade-offs to find a set of optimal and feasible solutions, each representing a candidate treatment list

(Figure 8). The best subset of the solutions that satisfy financial constraints and performance and risk targets are then selected for further evaluation and trade-off analysis. The selected treatments are then applied to update defined performance measures for the following planning period. In multi-year planning scenarios, this process is repeated every year throughout the planning period. Scenario analysis results are then summarized and used to support decisions on treatment selections, development of project candidates, and program development.

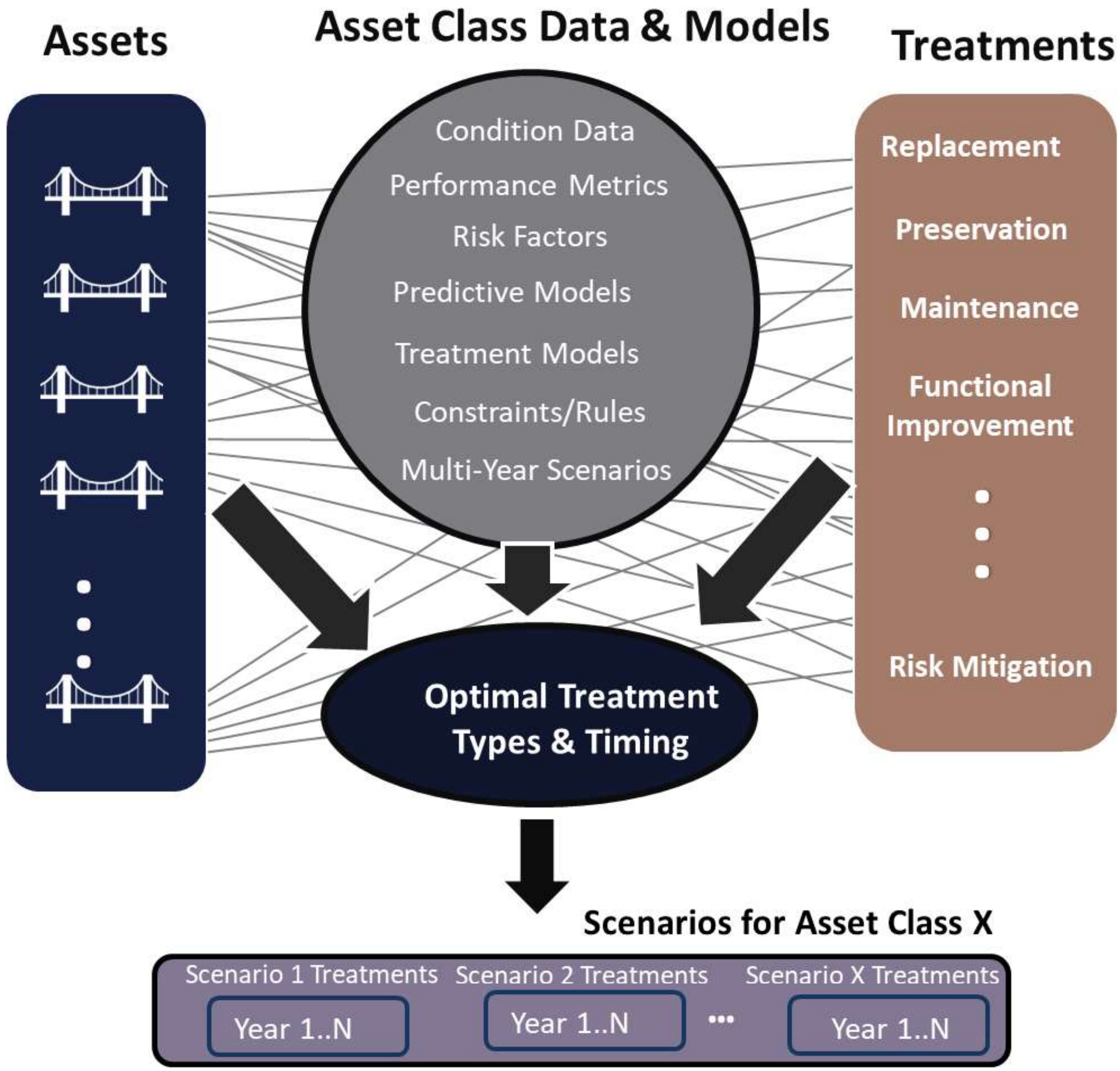


Figure 8: Using data, models, and scenarios to search for optimal treatments for each asset

7 System-Level Investment Trade-off Analysis

Optimized scenarios help to establish a quantitative relationship between investment levels and performance measures, based on defined lifecycle models and treatment strategies for each asset class. These scenarios will provide input to perform more detailed system-level trade-off analysis across multiple asset classes. Subsequent system-level analysis goes beyond individual asset classes to compare investment requirements against performance outcomes, and select projects to achieve the maximum return of investment with respect to maximization of performance within funding constraints across the entire asset portfolio. Results from multiple planning scenarios will be used to identify optimal and balanced budget allocations, which would inform and justify programming and budgeting decisions to accomplish performance objectives at lowest costs. Trade-off analysis of various scenarios will also help to accurately evaluate funding needs and the impact of different investment strategies.

7.1 "What If" Scenarios for Funding, Performance, and Needs Analysis

Planning scenarios are used to assess (or simulate) the impact of various decisions and investment strategies, and investigate a wide range of trade-offs. "What if" scenarios are defined for each individual asset class. Two types of planning scenarios can be defined (Figure 9): (1) funding scenarios to evaluate the impact of funding levels on system-wide performance and risk measures; and (2) performance target scenarios to evaluate minimum funding requirements to achieve certain performance or risk targets. System-level performance and risk measures are calculated using a weighted average based on some asset-specific attribute. For example, system-level average condition of a bridge inventory can be calculated using the deck area as a relative asset weight. Similarly, the total lane-mile of pavement segments can represent relative weights for pavements. The objective functions in the optimization model assure that:

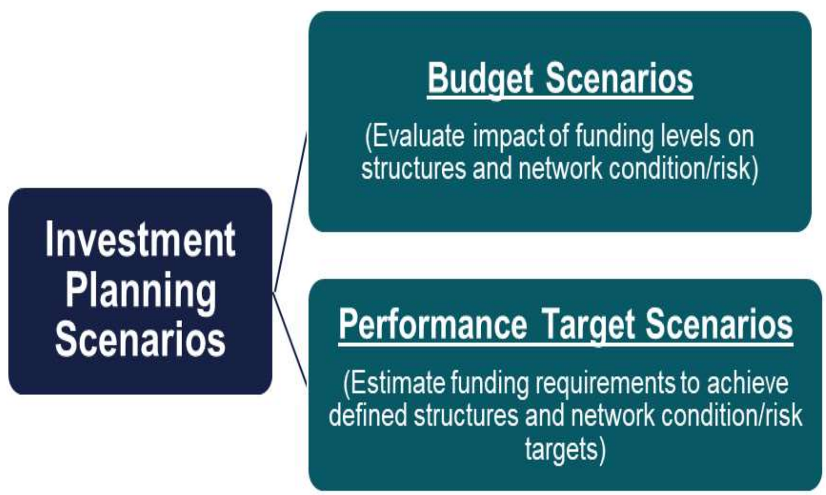


Figure 9: Types of "what if" investment scenarios

- For a budget scenario, the recommended treatments would provide the best possible performance at the given budget; and

- For a performance target scenario, the recommended treatments would meet the performance or risk target at the lowest possible cost.

Scenario analysis is used to support decisions to allocate funding among competing projects across different asset classes, taking into consideration different types of asset treatment needs, performance objectives, and financial constraints. Analysis can be undertaken for the entire system-wide asset class or any set of specific assets, by district, region, corridor, or specific groups of assets, e.g., interstate, NHS. The following are some examples of using “what if” scenarios for analysis:

1. **Funding Level versus Performance Measures Trade-Offs.** Scenario analysis determines the impact of funding levels on system-level performance measures over the planning horizon. It will determine the impact of varying funding levels on performance measures, and also determine the minimum funding requirements to meet defined performance targets (if feasible).
2. **Performance Target Setting.** Scenario analysis can be used to assess baseline performance measures, investigate the feasibility of performance targets under different financial constraints, and determine required investments to meet those targets. Comparing predicted performance measures against desired targets for different asset classes would also provide insights into required investment levels to meet targets, and can guide decisions on adjusting the targets if needed.
3. **Needs Analysis.** Scenarios can be used to evaluate treatment needs (or backlog) identified for different asset classes, and calculate performance outcomes and required funding to meet these needs. Needs records include information on treatment type, estimated costs, and proposed treatment date. For this analysis, the list of needs can be “forced” into the scenarios, and the analysis will determine the expected performance outcomes as well as the funding requirements and optimal timing for each need. It will also determine additional treatments that can be used.
4. **Evaluate Impact of Current and Planned Projects on Performance Measures.** Ongoing or committed projects can be considered, or forced-to, the scenario analysis. For these “forced” projects, the treatment types and times of these projects will take precedence over optimized treatments.

Figure 10 shows the use of asset class-specific scenarios to support system-level and program-level trade-off analysis. The following two sections describe two types of system-level analysis:

1. Capital versus Maintenance Investment Trade-off Analysis (Section 7.2).
2. Cross-Asset Budget Allocation Trade-off Analysis (Section 7.3).

Results of scenario analysis for Caltrans SHS bridges and pavements are used to demonstrate these system-level analyses in the next sections. Therefore, it is recommended that readers review Appendices A and B prior to reading the next sections.

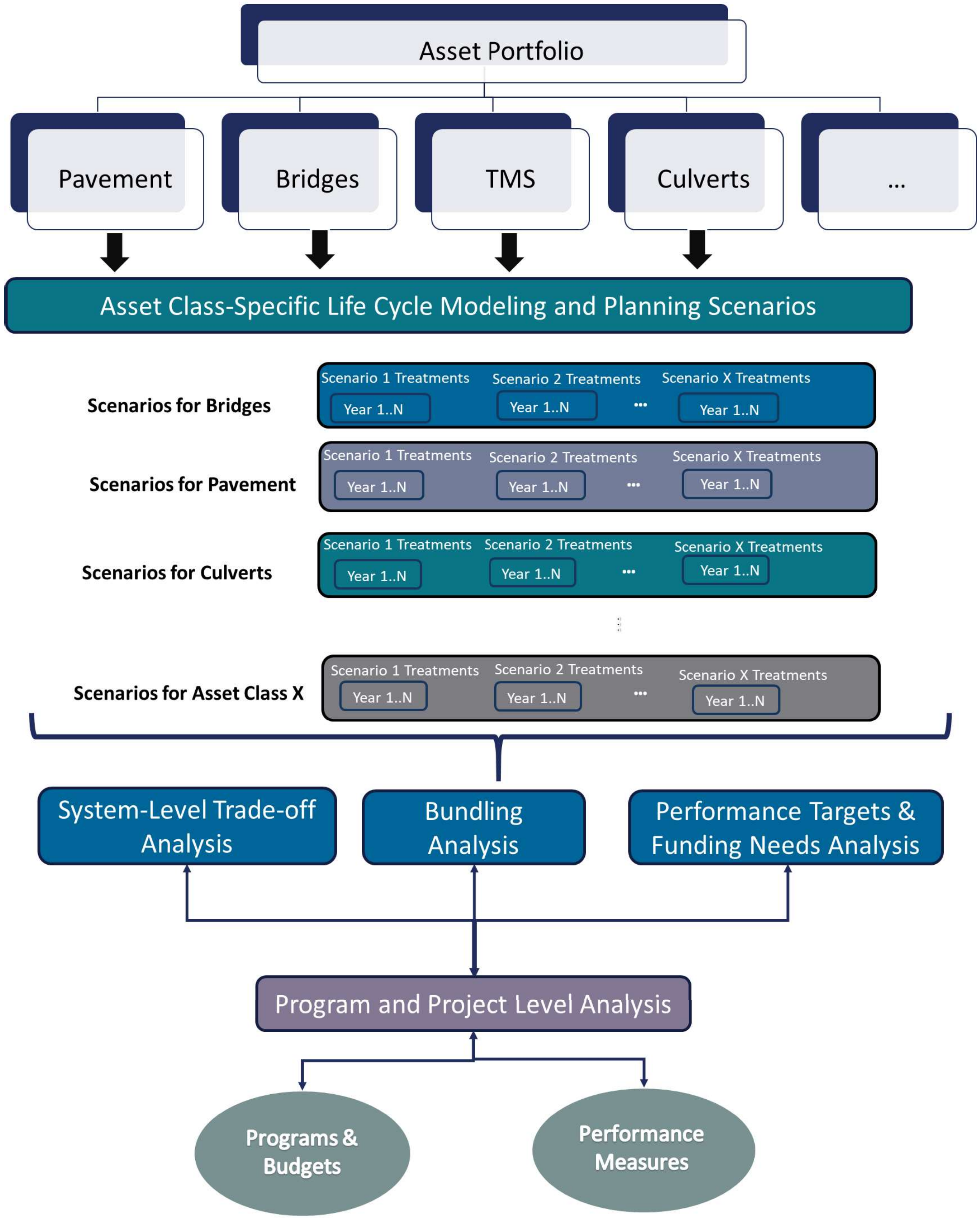


Figure 10: Using asset class-specific scenario results to support cross-asset analysis

7.2 Capital versus Maintenance Investment Levels Trade-off Analysis

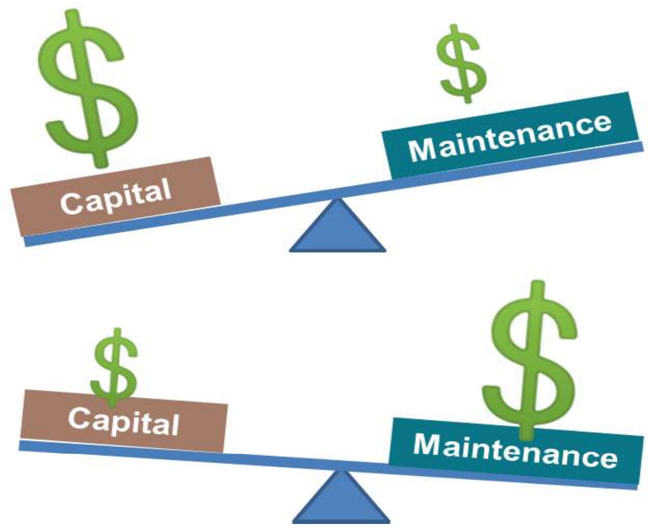


Figure 11: Need for analyzing proper balance between capital and operational expenditures

One of the important investment trade-offs concerns achieving the right balance between capital expenditures (or CapEx) and operational and maintenance expenditures (or OpEx) levels of investment. Decreasing capital investments for assets rehabilitation and reconstruction will lead to an increase in required maintenance funding due to increased need for emergency and unforeseen repairs (Figure 11). An optimal balance between capital and maintenance investment would achieve the best overall system-level performance at the lowest total investment (or Totex, which is defined as CapEx + OpEx). The treatments selected through the optimization of scenarios for a specific asset class can provide the basis for the CapEx/OpEx trade-off analysis.

The planning scenarios described in the previous sections represent asset class-specific CapEx investment levels, which result in specific performance measures for each asset over the planning timeframe. These performance measures can be used to estimate corresponding annual maintenance and operational needs (or OpEx) based on historical records and local expertise. Knowing the CapEx and corresponding OpEx investment levels for each scenario, the overall cost (Totex) versus the associated system-level performance measure can be examined to find the best balance.

For each asset class, the results from each scenario can be used to calculate an annual average cost and an annual average system-level condition. Figure 12 shows a conceptual trade-off between CapEx and OpEx expenditures and possible impact on system-level performance. Analyzing this trade-off can be performed by calculating the expected operational expenditure (OpEx) for each defined CapEx planning scenario. OpEx is estimated in two parts: fixed cost and maintenance cost components. The fixed cost component is assumed to include all operation costs independent of assets condition (e.g., staff, equipment, ongoing operations costs).

The maintenance cost can be defined as a function of asset condition, which can be estimated based on historical maintenance records. In our analysis, an average unit cost was assumed for assets within a certain condition state. The impact of different combinations on the average system-level condition was then determined, where the lowest Totex value would indicate the ideal CapEx/OpEx balance.

In absence of historical maintenance costs in our analysis, we made assumptions for the two asset classes we considered. For bridges, we assumed two types of maintenance activities: major and minor maintenance. Major maintenance cost is assumed to be $50 / sq. ft. of deck area, which is close to the cost of deck overlay, whereas minor maintenance cost is assumed to be $8/sq. ft., which is close to the typical cost of deck repair. The average condition index of bridges requiring minor maintenance was assumed to range between 20 and 30, whereas major maintenance would be applicable for bridges with condition index less than 20, using the condition rating scale that ranges between 0 (fail) and 55 (as new), as described in detail in Appendix A on bridges lifecycle modeling and shown in Equation 1.

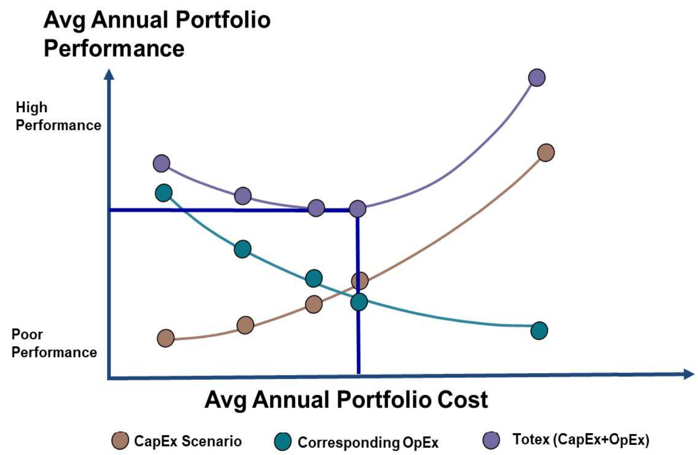


Figure 12: Conceptual view of CapEx/OpEx trade-offs, showing optimal performance-Totex balance

Bridge Condition Index = 55 - (A+B+C+E)　　　　　Equation 1

Where, A, B, C, and E are reduction factors based on the condition of the superstructure, substructure, deck, and inventory load rating, respectively.

Based on these assumptions, the average annual maintenance cost was calculated for each bridge planning scenario. Figure 13 shows the average annual expected capital and maintenance costs expected for each of the bridge scenarios. Table 2 shows the values of average annual costs for each planning scenario, and expected average annual system-level condition index of the SHS bridge inventory.

Table 2. Average CapEx, OpEx, Totex, and Condition Index for Bridge Scenarios

Scenario	Annual Avg Capex	Annual Avg Opex	Annual Avg Totex	BCI
Do_Nothing	$0	$1,726,512,192	$1,726,512,192	35.05
800_Million	$798,364,379	$1,157,314,470	$1,955,678,848	37.33
ConditionIndex_43	$6,484,520,558	$58,257,364	$6,542,777,922	42.4
SHOPP_10Yrs	$577,056,480	$1,262,699,352	$1,839,755,832	36.91
1_B	$994,579,374	$1,098,391,976	$2,092,971,350	37.64
600_Million	$599,985,782	$1,288,353,778	$1,888,339,560	36.84
800M_1.5B	$1,045,447,692	$1,133,183,047	$2,178,630,739	37.54
1B_2B	$1,417,918,949	$1,011,820,367	$2,429,739,316	38.07
RiskIndex_32	$5,117,173,973	$153,343,319	$5,270,517,293	41.71
Average	**$1,892,783,021**	**$987,763,985**	**$2,880,547,006**	**38.17**

Figure 14 shows the CapEx/OpEx trade-offs for each planning scenario. It can be seen that the $1.0 billion scenario achieves the best balance.

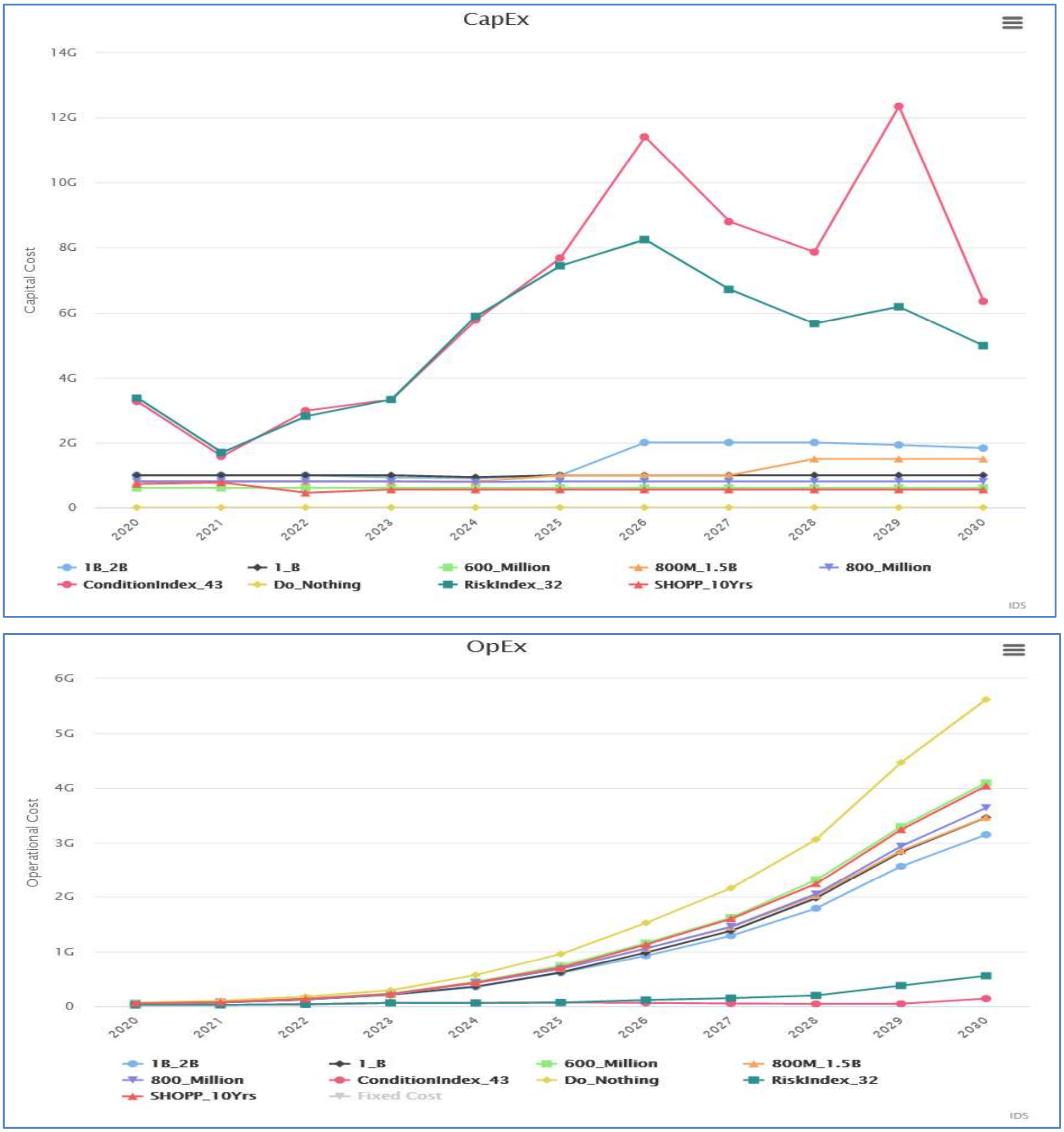


Figure 13: Average Annual CapEx and OpEx Costs for Analyzed Bridge Scenarios

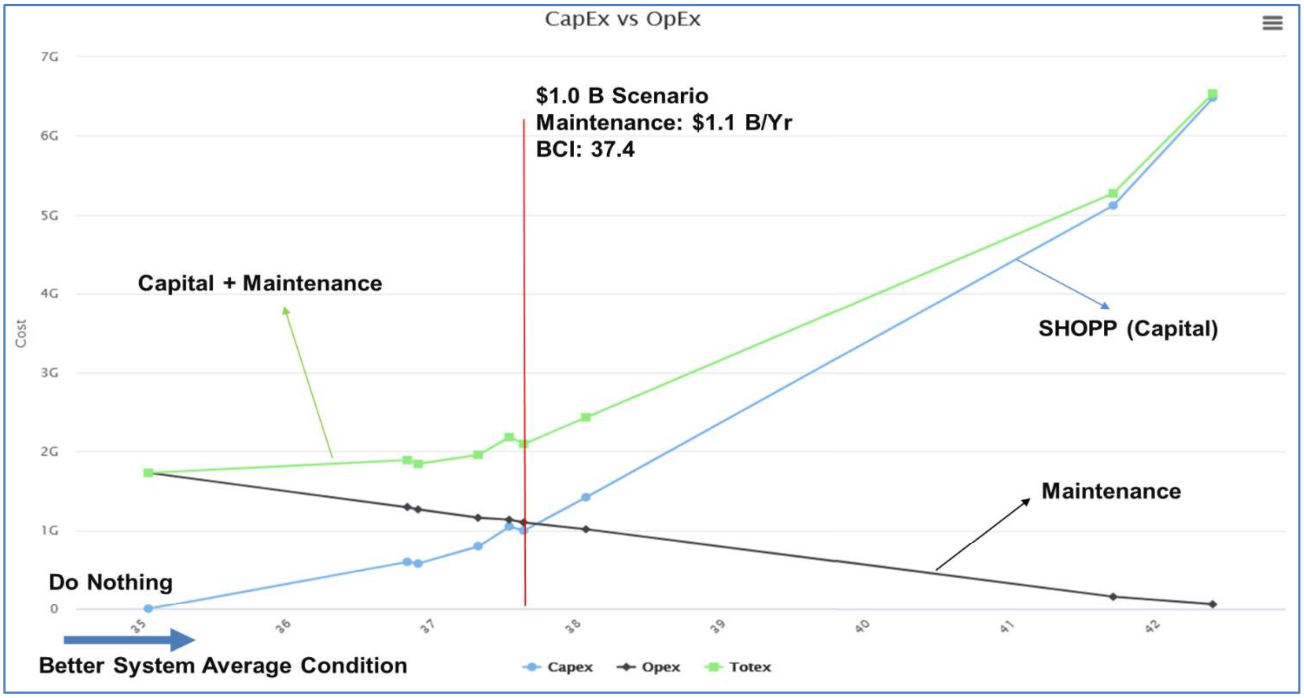


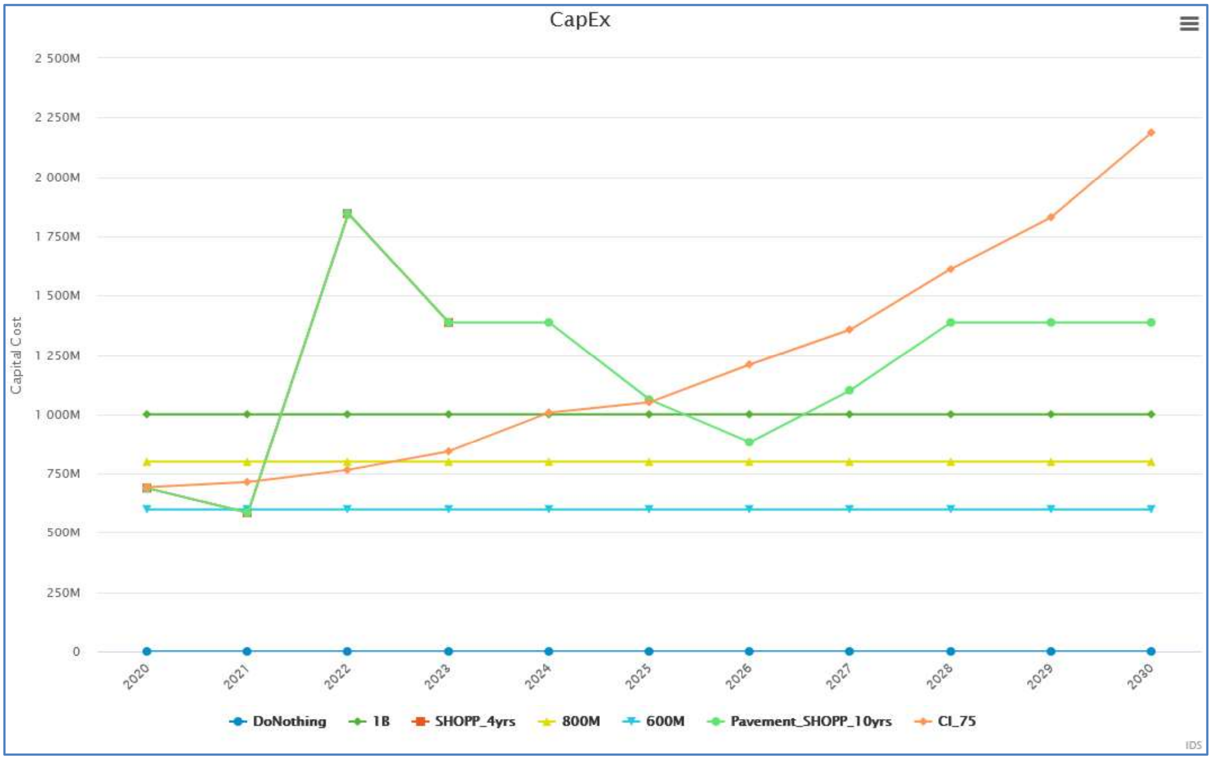
Figure 14: CapEx/OpEx Trade-Offs of SHS Bridge Scenarios

Similar analysis was performed for SHS pavement scenarios. We assumed two types of pavement maintenance activities: major and minor maintenance. Major maintenance cost is assumed to be $400,000 / lane mile, which is close to the cost of medium overlay. Minor maintenance cost is assumed to be $200,000 / lane mile, which is close to the typical cost of thin overlay. The average pavement condition index requiring minor maintenance was assumed to range between 30 and 50, whereas major maintenance would be applicable for pavement segments with condition index less than 30, using the PCI_2 condition rating scale (0: fail to 100: as new), which is calculated as shown in Equations 2 and 3, for AC and concrete pavement, respectively, and described in detail in Appendix B on pavement lifecycle modeling.

PCI_2_{AC} = 0.4* Roughness Index +0.4* Cracking Index + 0.2* Rutting Index
Equation 2

$PCI\_2_{JPCP\ and\ CRCP}$ = 0.4* Roughness Index +0.4* Cracking Index + 0.2* Faulting Index
Equation 3

Based on these assumptions, the average annual maintenance cost was calculated for each planning scenario. Figure 15 shows the average annual expected capital and maintenance costs expected for each of the pavement scenarios. Table 3 shows the values of average annual costs for each planning scenario, and expected average annual system-level condition index of the SHS pavement inventory. Figure 16 shows the CapEx/OpEx trade-offs for each pavement scenario. It can be seen that the SHOPP 4-Year scenario achieves the best balance.



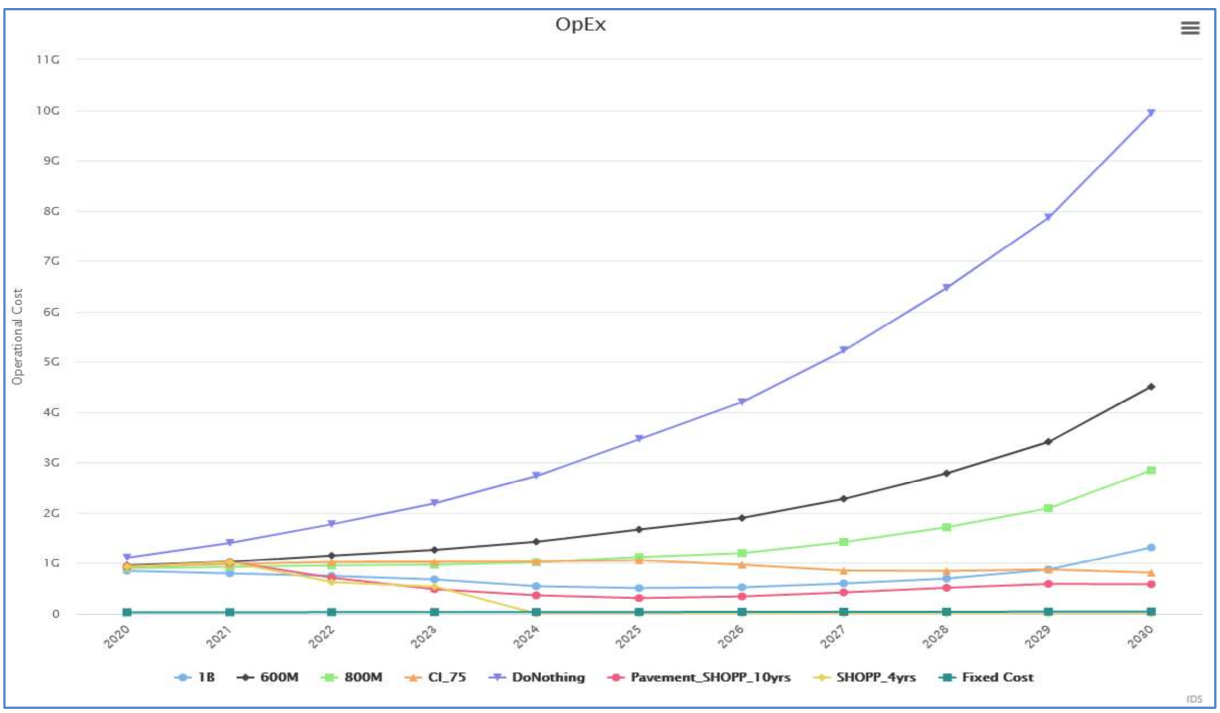


Figure 15: Average Annual SHOPP (CapEx) and Maintenance (OpEx) Costs for Pavement Scenarios

Table 3. Average Annual CapEx/OpEx/Totex and Condition Index for Pavement Scenario

Scenario	Annual Avg Capex	Annual Avg Opex	Annual Avg Totex	PCI
DoNothing	$0	$4,216,666,907	$4,216,666,907	60.39
1B	$999,999,762	$738,036,683	$1,738,036,445	75.72
SHOPP_4yrs	$1,126,749,633	$282,313,911	$1,409,063,544	76.38
800M	$799,999,719	$1,379,934,914	$2,179,934,634	72.13
600M	$599,999,633	$2,035,785,773	$2,635,785,407	68.98
Pavement_SHOPP_10yrs	$1,190,941,533	$569,184,084	$1,760,125,617	78.34
CI_75	$1,206,451,495	$947,023,165	$2,153,474,660	75.01
Average	**$846,305,968**	**$1,452,706,491**	**$2,299,012,459**	**72.42**

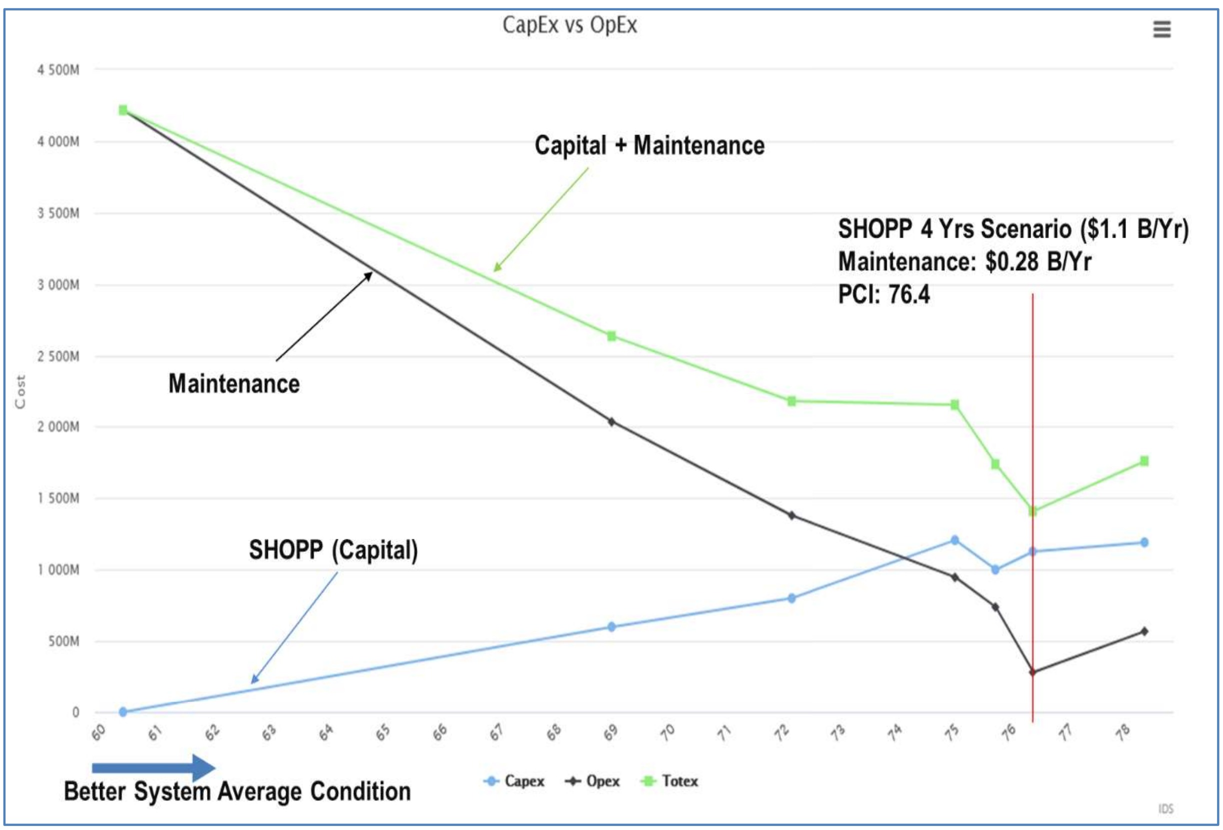


Figure 16: Capex/OpEx Trade-Offs of SHS Pavement Scenarios

Analysis of capital and maintenance trade-offs shows the most balanced investment scenarios with respect to CapEx/OpEx trade-offs. These scenarios will be considered for further analysis in subsequent steps.

7.3 Cross-Asset Budget Allocation Trade-off Analysis

In this step, we go beyond asset class silos to assess trade-offs of investment distributions among different asset classes. While assessing the performance of a specific asset class can be performed using well-known and widely accepted measures and analysis methods, assessing the performance of a portfolio of disparate assets is not as straightforward. There have been a number of efforts to develop a consistent approach to deal with this challenge [18]. One approach [19] recommended transforming different assets into "equivalent" asset (e.g., transforming bridges as equivalent pavement segments), and then use performance measures for the equivalent assets to allocate budget. Another approach [20] suggested formulating the problem as a linear combination of objectives and constraints for each asset type. In addition to the lack of details in the literature or evidence of validating these approaches, no clear methodology for practical application was provided in available literature.

Current practices for allocating budgets among multiple asset classes are still largely based on legacy or historical basis, which may not reflect the actual performance needs if the asset portfolio is considered in its entirety. In this project, we propose an optimization approach to allocate the overall available budget among different asset classes based on the maximization of the overall performance of the entire asset portfolio. In essence, this approach finds the ideal balance of funding allocation across different asset classes. The cross-asset trade-off analysis utilizes the results of various planning scenarios that have been generated in the previous steps (Figure 17).

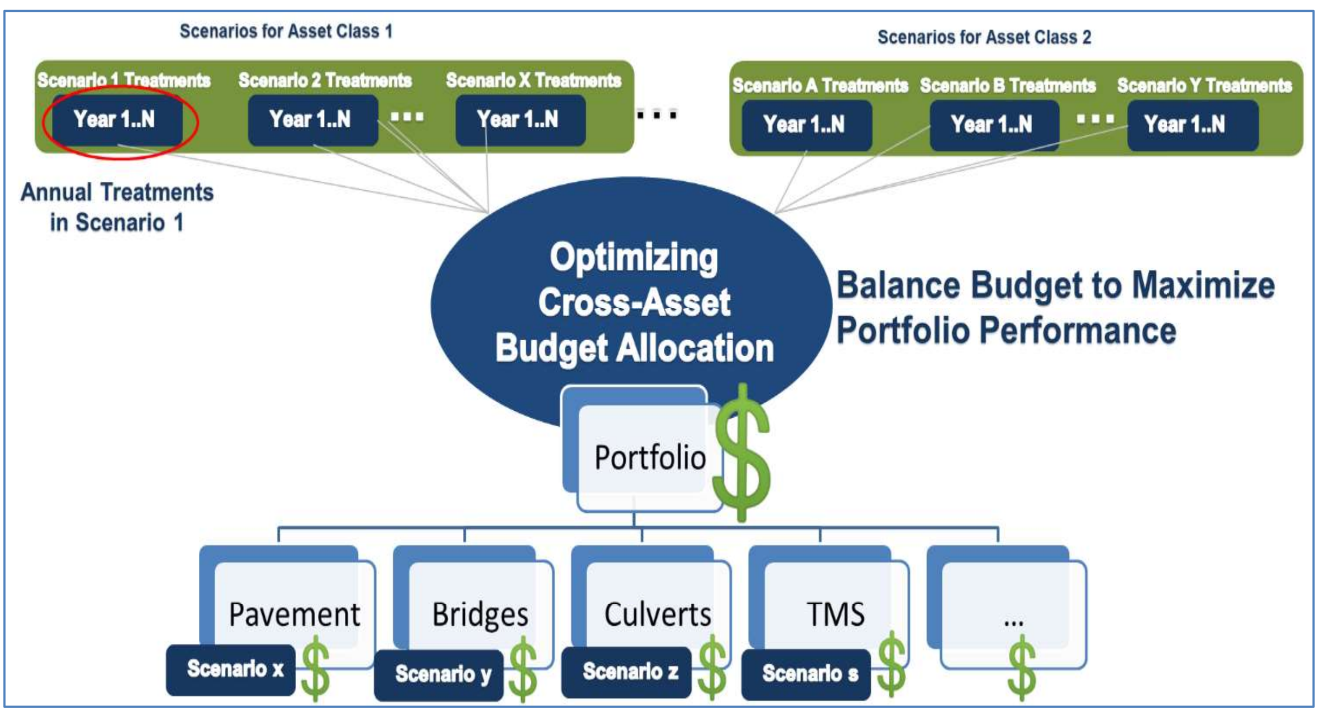


Figure 17: Using scenario results to optimize budget allocation among multiple asset classes

We propose a 3-step procedure for finding optimal portfolio budget allocation (Figure 18). Starting with the set of scenarios previously analyzed for each asset class, this procedure finds the best split of available total budget among different asset classes to maximize the overall portfolio performance. In essence, this procedure determines the optimal combination of scenarios (one scenario per asset class) that maximize the assets portfolio overall performance at any given total budget. The impact of varying budget allocations to different asset classes on the overall portfolio performance is then examined. Figure 18 shows the three main steps that are performed to determine optimal cross-asset budget allocation. A summary of these steps is provided below.

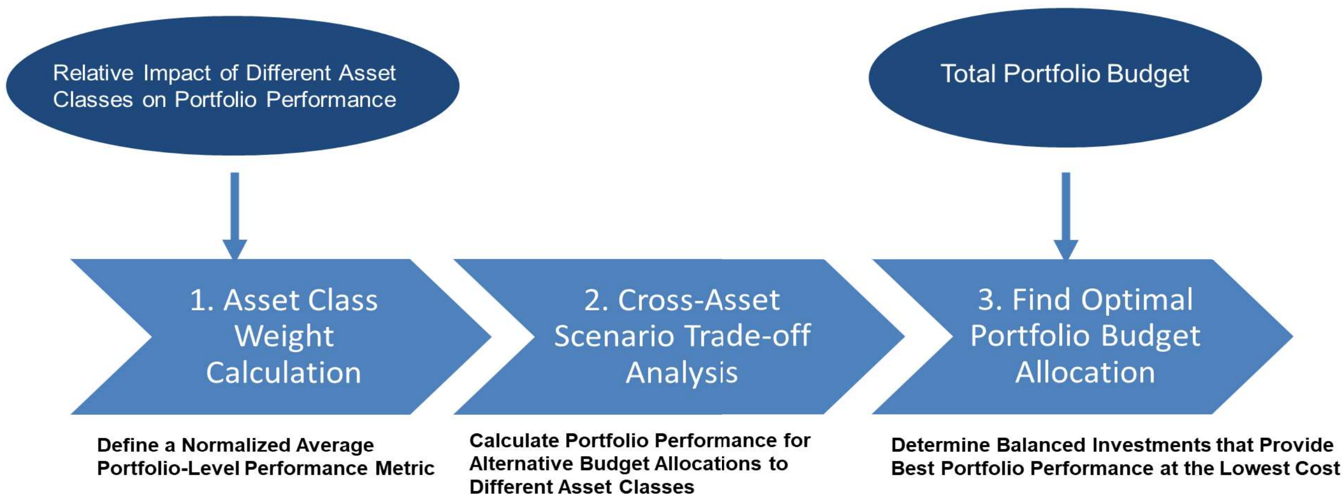


Figure 18: Steps performed to find optimal budget distribution among different asset classes.

7.3.1 Determine Relative Weighting of Asset Classes for Portfolio Level Analysis

The definition of a normalized cross-asset performance measure requires the consideration of a relative weighting of asset classes. The weightings represent the relative value, importance, size, criticality, or impact of a particular asset class on the performance of the entire asset portfolio. Although quantifying assets relative weightings can be easily performed for assets in the same class (as was done for bridges and pavement), determining a relative weighting of different asset classes would require the use of a semi-heuristic approach. In essence, the purpose of this weighting is to answer the question: which asset class is the most important under the defined criteria, and what is the relative ranking of these classes based on their contribution to the entire asset portfolio.

Assigning weightings to asset classes can be performed using the analytic hierarchy process (AHP) approach [21], where qualitative pairwise ratings or preference can be defined. However, in an attempt to employ a more objective approach, we used a simple model to determine these weightings based on quantitative metrics such as the asset class replacement value and the average annual lifecycle cost required to maintain the asset class in a state of good repair or meet performance targets. In our analysis, we considered two factors to calculate relative asset class weights. The following subsections describe these factors.

7.3.1.1 Assets Average Annual Life Cycle Cost

The average annual lifecycle cost (AALC) can be calculated based on the planning scenarios for maintaining current condition state or the minimum investment level to achieve performance targets. For both SHS bridges and pavements classes, we generated a set of scenarios to assess minimum funding levels required to maintain current (2020) status-quo system-level weighted average condition measure, as discussed in Appendices A and B. The CI_43 bridge scenario and the CI_75 pavement scenario determined the annual investment levels required to maintain average status quo condition state over 10-year planning horizon (Average BCI of 43 and average PCI of 75). These scenarios showed that the AALC for bridge and pavement inventory are $6.1 billion and $1.2 billion, respectively (Table 4).

Table 4. Summary of AALC Calculated for SHS Bridge and Pavement Inventory

Asset Class	10-Year Status Quo Condition Scenario	AALC
Bridges	CI_43	$6.1 billion
Pavement	CI_75	$1.2 billion

7.3.1.2 Assets Replacement Value

This factor implicitly assumes that the needs to maintain and improve assets is proportional to their replacement value. The current replacement value of SHS bridges and pavements asset classes were calculated using a simplified asset valuation approach, based on the estimated remaining service life and the current replacement cost of each asset class. The remaining service life has been estimated based on the average useful life of assets and their current age, or based on the current condition state of the assets (where remaining service life is estimated based on assets condition).

For example, Caltrans SHS bridge inventory has approximately 244 million square feet of deck area, and an average age of 37.5 years. Assuming an average 60 years of service life for a typical bridge (i.e., the current remaining service life is approximately 38%), and $635 per square foot of new replacement with a modern equivalent bridge, the current replacement value of the bridge inventory considering accumulated depreciation would be approximately $58 billion.

A similar age-based approach was used to estimate the remaining service life of pavement assets. Caltrans SHS includes 37,355 lane miles of AC pavement, with replacement cost of $1.002 million per lane mile, and 12,932 lane miles of JPCP and CRCP pavement, with replacement cost of $2.6 million per lane mile, as described in the pavement treatment models Appendix B. The approximate service life of AC and concrete surfaces was estimated to be 20 and 40 years, respectively [22]. The total replacement cost of the AC and concrete inventory with modern equivalent pavement assets is approximately $37.4 billion and $33.6 billion, respectively (total $71 billion). Estimating the current age of pavement surfaces can be derived from the condition (in absence of the last resurface or construction year in the data set). The current distribution of pavement condition, as described in Appendix B, was found to be: 45% good, 53% fair, and 2% poor for AC pavement; 36% good, 61% fair, and 4% poor for JPCP pavement; and 52% good, 45% fair, and 3% poor for CRCP pavement. Considering the average remaining life based on condition state to be 85%, 70%, and 20% for pavement in good, fair, and poor condition, respectively, the average remaining service life can be calculated as shown in Table 5 below. Therefore, the current replacement value of the SHS pavement assets under consideration can be estimated to be $53 billion. Therefore, the portfolio total replacement value comes to $111 billion, and the total average annual lifecycle cost is $7.3 billion.

Table 5. Total Replacement Value calculation for SHS Bridges and Pavements

Asset Class	**Avg Service Life**	**Avg Age**	**Avg Rem. Life %**	**Total Qty**	**Unit Cost**	**As New Value**	**Replacement Value**
Bridges	60	37.5	38%	244 Million sq. ft	$635/sq. ft	$155 billion	$58.8 billion
HMA	20	4.5	76%	37,356 Lane Miles	$1.002 M/ Lane Mile	$37.4 billion	$28.4 billion
JPCP	40	10.4	74%	12,115 Lane Miles	$2.6 M/ Lane Mile	$31.5 billion	$23.3 billion
CRCP	40	9.5	76%	817 Lane Miles	$2.6 M/ Lane Mile	$2.1 billion	$1.6 billion

7.3.1.3 Calculation of Relative Asset Class Weights

Once the two weighting factors are calculated for each asset class, relative asset class weights can be calculated using Equation 4.

$$W_j = \frac{AALC_j}{\sum_{i=0}^{N} AALC_i} * W_{AALC} + \frac{Replacment\ Value_j}{\sum_{i=0}^{N} Relacement\ Value_i} * W_{Replacement\ Value} \qquad \text{Equation 4}$$

where,

$W_j = Relative\ weight\ of\ asset\ class\ j$

N = Number of asset classes considered in the analysis

$AALC_j\ and\ \ Replacment\ Value_j$ are the average annual lifecycle cost and replacement value of asset class j

W_{AALC} and $W_{Replacement\ Value}$ are optional weightings that could be assigned for each of the two factors considered to estimate asset class relative weightings. respectively.

$W_{AALC}\ and\ W_{Replacement\ Value}$ are optional user-defined weightings for each of the parameters considered. Assuming equal weighting (50%) for the AALC and Replacement Value parameters, the relative weight for SHS bridge and pavement asset classes can be calculated as follows:

$$W_{Bridges} = \frac{58}{111} * 0.5 + \frac{6.1}{7.3} * 0.5 = 0.67$$

$$W_{Pavement} = \frac{53}{111} * 0.5 + \frac{1.2}{7.3} * 0.5 = 0.32$$

However, we could choose to assign weightings for the parameters if they have different impact on the relative importance of asset classes on the overall asset portfolio performance. For example, if we assume 70% and 30% relative weighting for the AALC and Replacement Value parameters, the relative weight for SHS bridge and pavement asset classes will be calculated to be 0.62 and 0.38, respectively. Assigning relative weights to asset class factors may be more important when considering a larger set of asset classes, with significantly different impact on the overall portfolio performance.

7.3.2 Cross-Asset Scenarios Trade-off Analysis

In our analysis, we used a normalized performance measure of the asset portfolio that can be rolled-up from the performance measures of individual assets, based on the weightings assumed for each asset type. For example, bridges and pavements used different condition rating scheme that ranged between 0 (fail) and 55 (new) for bridges, and between 0 (fail) and 100 (new) for pavements. A portfolio performance measure has been calculated by linearly scaling the condition index in each asset class to a common normalized portfolio performance measure (e.g., on a scale between 0 and 10), considering the relative weightings assumed for each asset class.

The scaled asset class condition index (ACI) can be calculated using Equation 5:

$$ACI_{Scaled} = Portfolio\_CI_{Failed\ Index} + (ACI - ACI_{Failed\ Index}) * \frac{Portfolio\_CI_{New\ Index} - Portfolio\_CI_{Failed\ Index}}{ACI_{New\ Index} - ACI_{Failed\ Index}} \quad \text{Equation 5}$$

where,

$Portfolio\_CI_{Failed\ Index} = Assumed\ "fail"\ portfolio\ index\ (i.e., when\ all\ assets\ are\ in$ fail $condition)$

$Portfolio\_CI_{New\ Index}$
$= Assumed\ "new"\ portfolio\ index\ (i.e., when\ all\ assets\ are\ in$ new $condition)$

$ACI_{Failed\ Index} = Assumed\ "fail"\ condition\ index\ for\ the\ asset\ class$

$ACI_{New\ Index} = Assumed\ "new"\ condition\ index\ for\ the\ asset\ class$

Considering an example of a bridge with a condition index BCI (S1 value) of 40, and a defined portfolio scale between 0 (fail) and 100 (new), its scaled condition index can be calculated as follows:

$$Bridge\ CI_{Scaled} = 0 + (40 - 0) * \frac{100 - 0}{55 - 0} = 72.7$$

After calculating the scaled condition index for each asset class, the average normalized portfolio performance measure can then be calculated based on the scaled condition index of assets multiplied by the relative weight of the respective asset class, as shown in Equation 6.

$$Portfolio\ Performance\ Measure\ = \sum_{i=0}^{N} Asset\ Class\ Average\ Scaled\ CI_i\ * W_{Asset\ Class\ i}$$ Equation 6

where,

N = Number of asset classes considered

$Asset\ Class\ Average\ Scaled\ CI_i$
$= Average\ annual\ scaled\ condition\ index\ for\ all\ assets\ in\ class\ i$

$W_{Asset\ Class\ i} = Relative\ weight\ of\ asset\ class\ i$

Based on the optimized scenarios developed for each asset class, the cross-asset trade-off analysis is performed by investigating “all” possible cross-asset scenario combinations to determine the overall portfolio performance in each year in the planning horizon. A typical combination of scenarios across different asset classes represents a possible distribution of a portfolio total budget among different asset classes.

For each combination of cross-asset scenarios, the average annual total portfolio investment (over all asset classes) along with the average annual portfolio performance measure are calculated. Figure 19 shows an example of cross-asset scenario combinations. It is obvious that the best trade-offs or optimal budget allocation would lie on the Pareto front (shown as red dots). Therefore, given any defined portfolio total budget, the optimal budget distribution can be determined, establishing the optimal investment levels (or scenario) for each asset class in the portfolio.

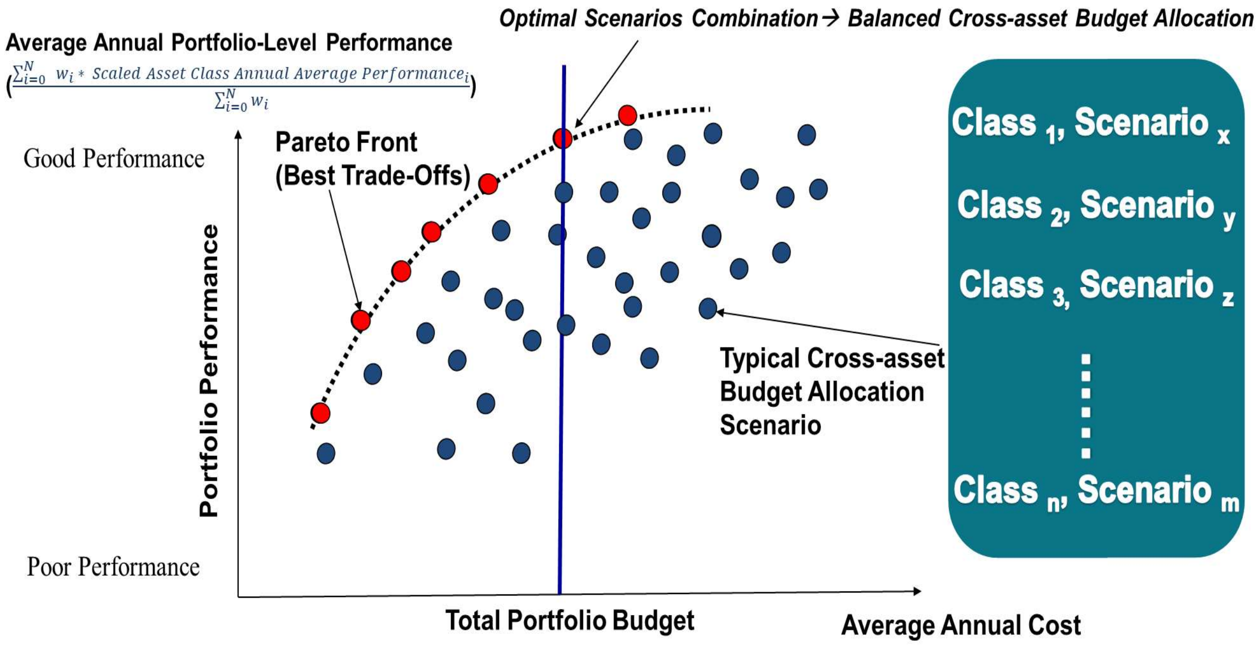


Figure 19: Evaluating all scenario combinations to optimize cross-asset budget allocation

7.3.3 Finding Optimal Budget Allocation Among Asset Classes

This step involves finding the best distribution of the total portfolio budget among different asset classes to provide the maximum overall portfolio performance. Considering the planning scenarios defined for SHS bridge and pavement inventory, and estimating a relative class weight of 0.6 and 0.4 for bridges and pavement, respectively, Figure 20 shows the distribution of the average annual portfolio performance measure and the average annual investment level for each bridge and pavement scenario combination. Each dot in this chart represents a unique combination of two scenarios, one for bridges and one for pavement. The following bridges and pavements scenarios were considered in this analysis:

- Bridges: \$600 million, \$800 million, \$ 1 billion, \$800 million stepped to \$1.5 billion, \$1 billion stepped to \$2 billion, and SHOPP 10 years.
- Pavements: \$600 million, \$800 million, \$1 billion, SHOPP 10 years, SHOPP 4 years.

For example, using an assumed total portfolio annual investment budget of \$2.2 billion, the optimal scenario combination (or budget splitting) can be determined (shown in red). The optimal scenario combination was found to be \$1 Billion for bridges, and the SHOPP 10-year scenario for pavement, which resulted in an average annual portfolio performance index of 72.4. It can be noticed that four other scenario combinations with approximately the same average annual investment of \$2 billion, however they produce a lower overall portfolio performance. One of these combinations (shown on the bottom right table) is \$800 million- \$1.5 billion bridge scenario and the pavement SHOPP 10-

year pavement scenario, which collectively produced a portfolio average annual performance of 72.29.

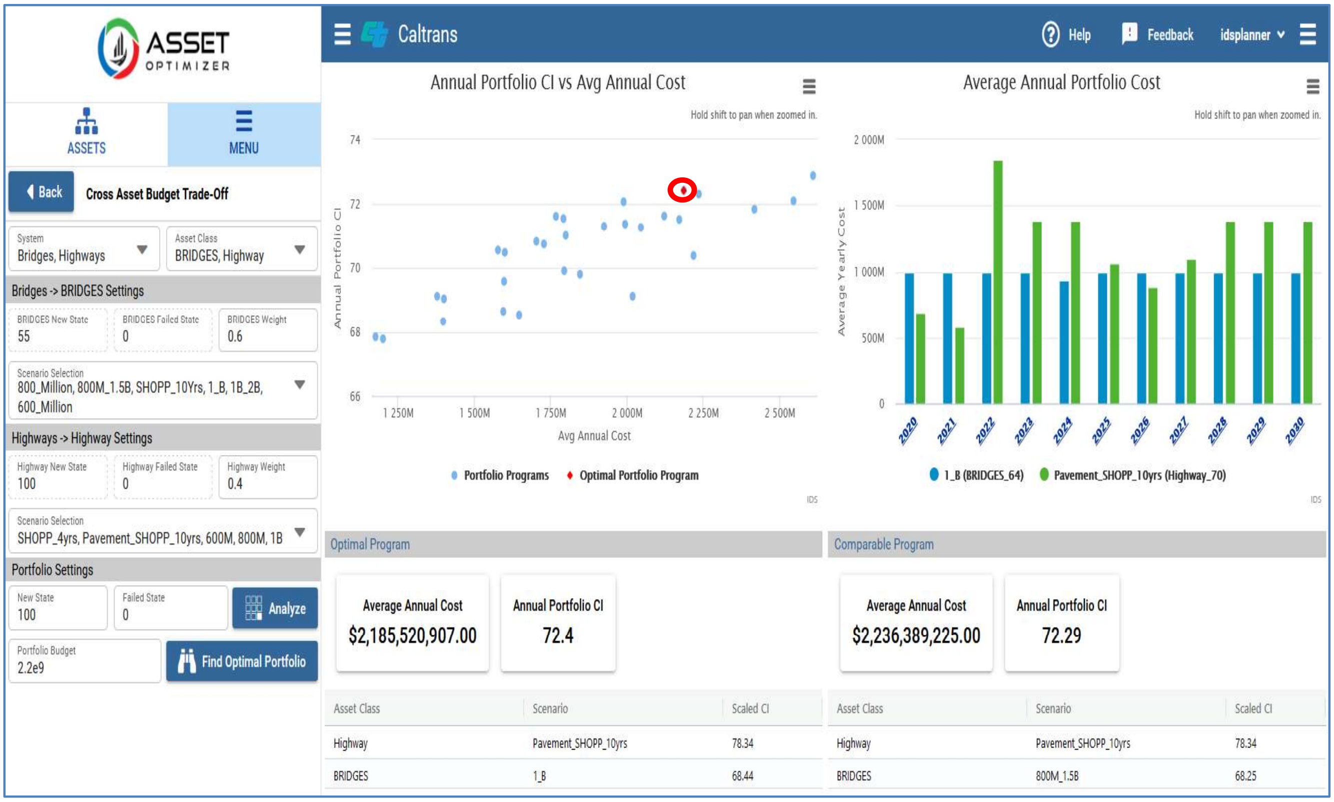


Figure 20: Example for optimizing budget allocation across Caltrans bridge and pavement asset classes given an average portfolio annual budget of $2.2 billion (optimal allocation shown in red)

8 Bundling Analysis

Cross-asset treatment types and timing identified from previous scenario optimization and needs analysis have been optimized considering trade-offs of performance and cost of individual asset classes. However, many of these individual treatments would have spatial and/or temporal relationships that would allow for improving efficiencies by bundling these treatments into common projects. Bundling these treatments into practical projects is an important step for determining and scoping project candidates. A number of benefits can be realized due to bunding, including:

1. Reducing work zone cost and risk, public disruption, agency and user costs;
2. Improving projects efficiency and coordination;
3. Allowing cost sharing across programs or organizations (e.g., local agencies); and
4. Achieving a positive impact on the public and environment.

Criteria for bundling of treatments typically include proximity and timing of individual treatments. Treatments on smaller or less expensive assets, such as guardrails and signs, can be bundled with adjacent larger projects (e.g., bridge or pavement rehabs). Multiple treatments on the same asset or on a set of assets in close proximity are often programmed into the same project to increase efficiencies by reducing mobilization and traffic management costs, public impact, and risks. Given the overhead costs, project scopes are required to be of practical size to be justified and programmed.

In this project, we implemented an innovative density-based spatial clustering algorithm to bundle treatments spatially and temporally. Bundling is based on measuring the spatial proximity of individual treatments, as well as the difference between the proposed years of these treatments. Bundles typically include treatments on multiple classes; however, they may also include treatments on different assets in the same asset class (e.g., deck repairs or overlay on adjacent bridges). Figure 21 shows an example of bundling parameters for bridge and pavement treatments identified under the state-wide SHOPP 10-year scenarios. Bundles were created to include treatments within 2-mile radius, that are recommended within the 10-year planning horizon (2021-2030). Bundling criteria may also specify specific asset groups or specific treatment types. Figure 22 shows an example map including bundles and treatments.

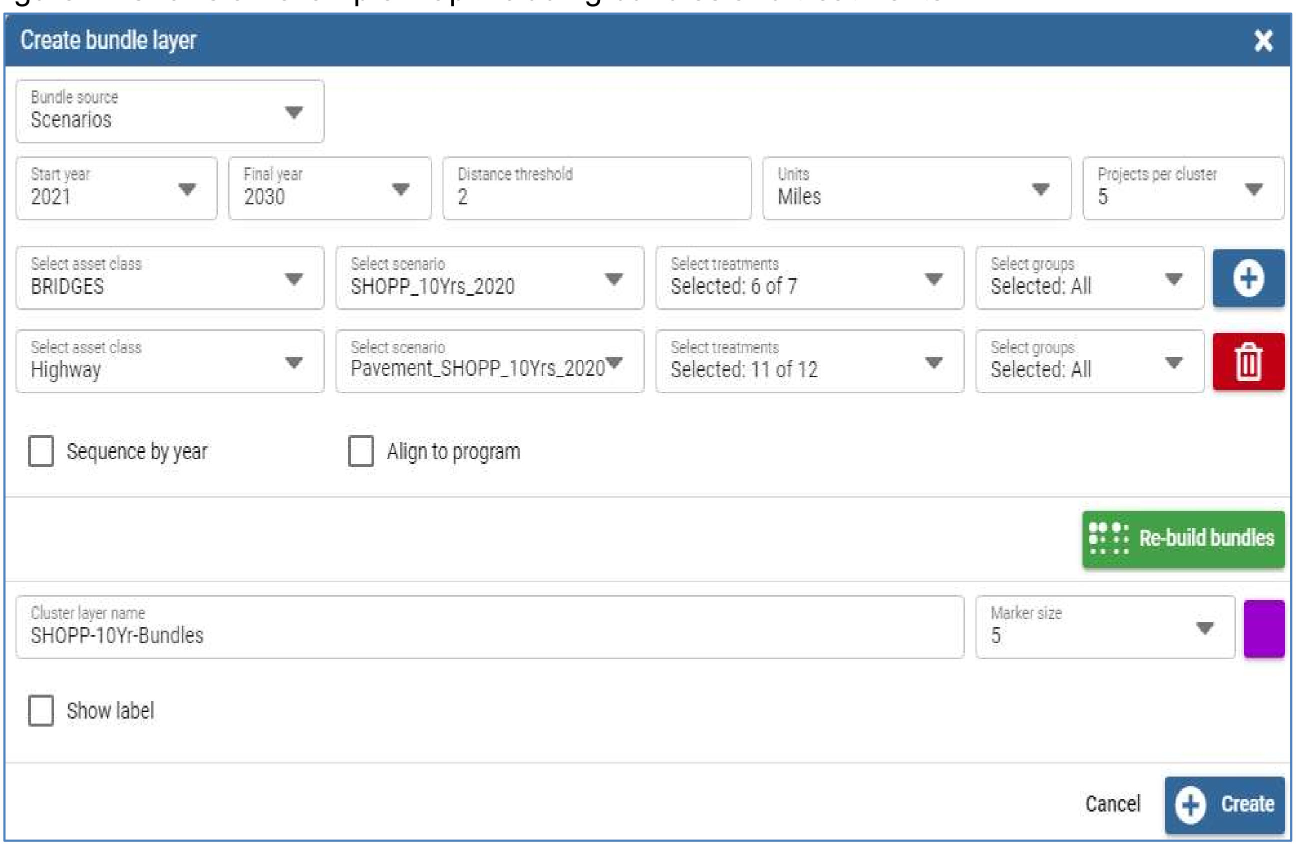


Figure 21: Example of cross-asset project bundles based on spatial and temporal constraints

Attributes of individual treatments within a bundle can be adjusted from the original optimization-based recommendation to fit practical project delivery requirements. Work types, scope, timing, and cost of individual treatments can be modified before grouping them into one project. For example, the total cost can be adjusted to reflect expected savings. Also, individual treatment work type, scope, or timing can be aligned. Project timing may require adjustment for funding availability, resource constraints, or need to coordinate with other projects (e.g., local agencies).

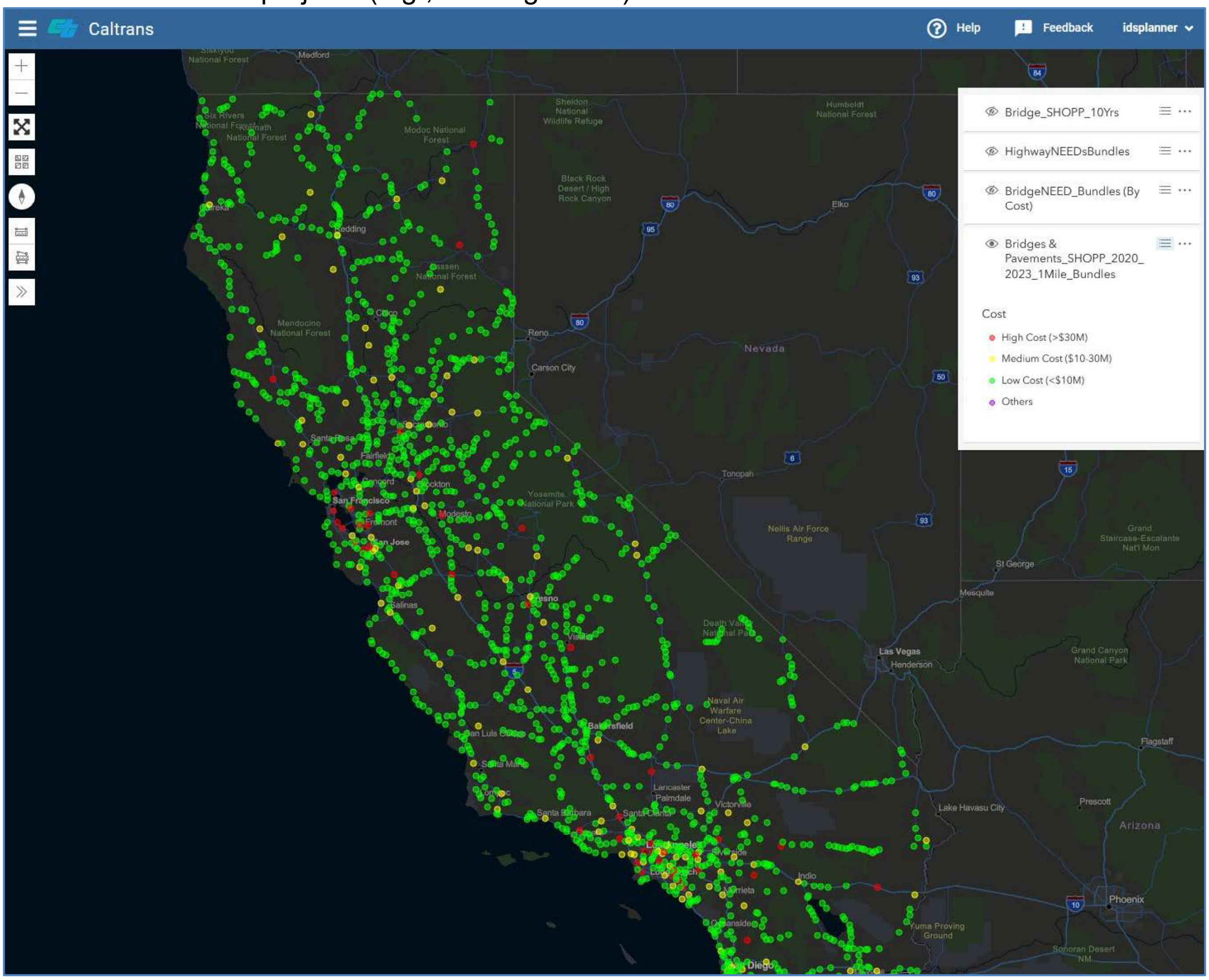


Figure 22: Example of cross-asset treatment bundles for bridge and pavement treatments recommended by the SHOPP 10-year planning scenario.

Identified treatment bundles can then be added to a pool of candidates, to be further evaluated for prioritization and possible nomination into programs. Bundled treatments can further be (re)evaluated using scenario analysis to assess the impact on performance measures and costs, taking into consideration any changes which may have been introduced to the original treatment type, timing, or costs (e.g., treatment deferrals). Similar to the process used for needs evaluation, the list of bundled treatments is “forced” into the scenario, which will compute funding levels and performance implications of the candidates.

9 Programming and Budgeting Process

Effective programming and budgeting decisions require the integration of project-level analysis and system-level cross-asset analysis. The proposed methodology achieves this integration through the use of asset class-level predictive performance models, system-level cross-asset scenario trade-off analysis, and bundling analysis to guide the identification of optimal project candidates, which are subsequently evaluated and prioritized using MODA value functions.

Multiple programs and funding sources can be defined, tracked, and managed. Programs are typically defined to focus on specific performance objectives, asset classes, work types, or to meet certain financial rules and constraints. Funding sources would include a variety of federal, state, or other funding to be allocated to different programs. Projects nominated into any program are analyzed and prioritized based on MODA program-level criteria and performance objectives. As projects progress and funds are committed and consumed, the status of projects and funds are continuously tracked and updated to allow for continuous evaluation or adjustments to the programs, and to enable timely decisions to ensure efficient project delivery and accurate reporting.

Figure 23 shows a proposed 8-step process for program development. The main steps of this process include:

1. **Define program goals, objectives, and performance targets.**
   Set up the program timeframe, objectives hierarchy, and determine appropriate MODA value functions and relative weightings. Define a set of feasible performance targets based on previous trade-off analyses as well as organizational objectives.

2. **Define program funding sources and rules.**
   Identify eligible funding sources, and determine or forecast initial funding levels and annual allocations to each program.

3. **Assemble initial set of project candidates.**
   Assemble a list of annual project candidates based on analyses of optimized treatments and treatment bundles identified from previous scenarios, cross-asset trade-off analysis, needs analysis, and bundling analysis. Project candidates are identified with consideration of program performance objectives and funding rules.

4. **Calculate project benefits.**

Based on program-specific performance objectives and project-level MODA value functions, gather project parameters and estimate project benefits.

5. **Perform project-level trade-off analysis.**
   Using project-level MODA, evaluate trade-offs of different project candidates, and select highest-value candidates in each program year.

6. **Evaluate project candidates.**
   Project candidates are evaluated against defined performance targets and funding limits using what-if scenario analysis. Analysis results would validate that performance accomplishments of the project portfolio meet the targets, and that estimated projects' costs are within allowed funding constraints.

7. **Finalize and nominate list of project candidates.**
   The project candidate list is revised by adding or removing projects or modifying projects scope, expected performance outcomes, and/or costs until performance targets are met within funding limits. Modifications of the project portfolio may require re-evaluation of benefits using MODA. Finalized project portfolio can then be nominated for program.

8. **Manage programs and budgets, and make adjustments as needed.**
   Projects and budgets are tracked and managed based on a pre-defined workflow throughout their delivery lifecycle, from nomination and approval through closure and acceptance. Projects' progress is continuously tracked, updated, and evaluated to ensure attainment of expected performance outcomes within available funding constraints. Funding sources and allocations to different programs and projects are also tracked and managed. Scenario analysis is used to perform periodic program evaluation, and guide decisions on any required program or budget adjustments.

The following sections describe some of the steps in more details.

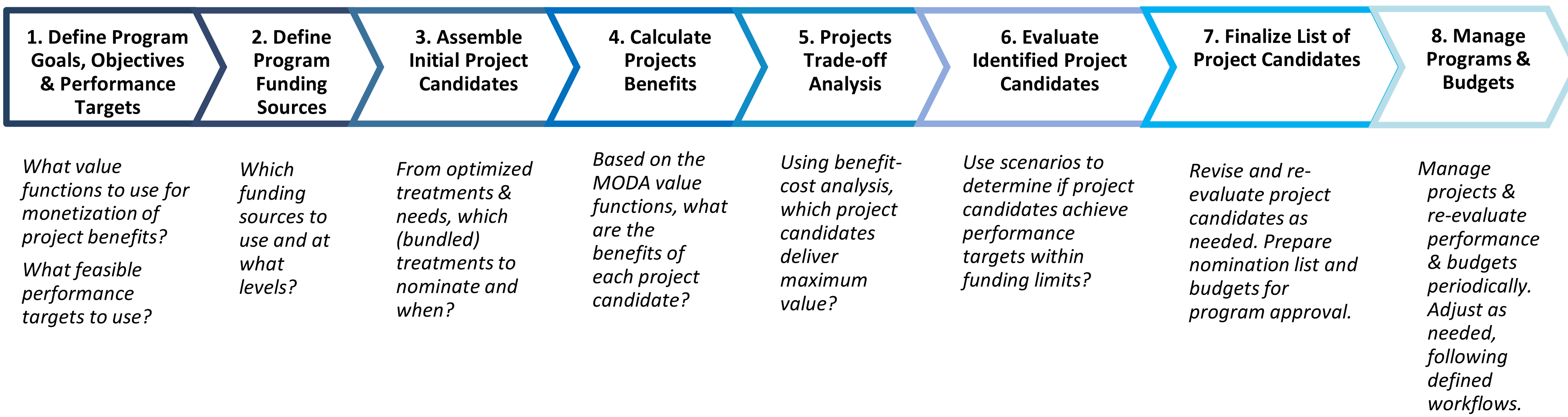


Figure 23: Key Steps for Program Development in the Proposed Methodology

9.1 Setting Performance Targets and Assembling Project Candidates

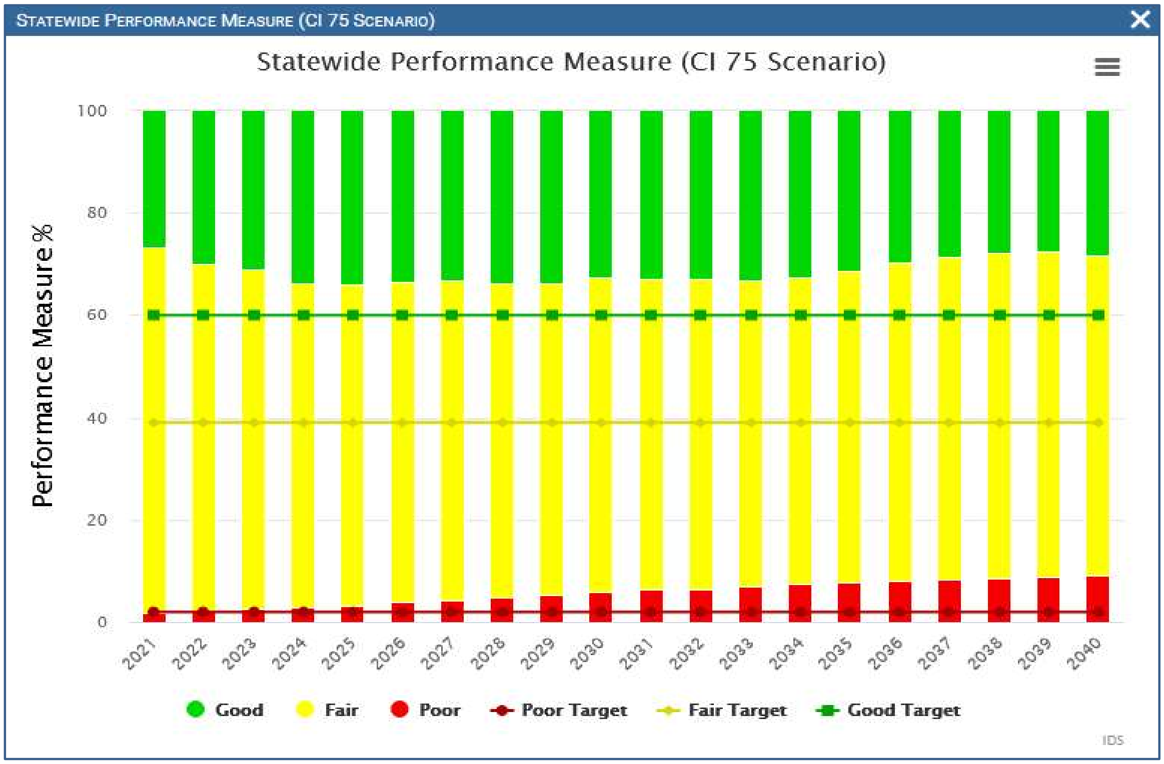
Performance objectives, along with defined targets, are used to justify program investments, and guide project selections and budgeting decisions. Several categories of performance objectives are typically used [23]. Performance objectives can be defined for the entire system or for a sub-system (e.g., on a district level or for a specific functional class).

Program performance measures include assets specific performance accomplishments such as asset preservation and condition improvements, enhanced capacity, or mitigating known risks and assets vulnerabilities. Asset-level performance measures are calculated for each individual asset, and then aggregated to system-level using appropriate asset weightings. Program performance objectives often span one or more organizational goals, that may not be directly associated with any specific assets (e.g., mobility, safety, sustainability). Some system-level measures are typically related to project benefits, which are used in MODA models. Other objectives may represent certain aspects of organizational performance such as levels of investment that promote transportation equity, environmental sustainability, and regional coordination.

Performance targets are important to monitor, benchmark, and report on performance accomplishments, and to ensure that the program is on track to meet performance targets. However, sometimes, performance targets are defined based on historical or desired performance, which may not be feasible or realistic to attain for the asset inventory within available funding. Without robust prediction of assets lifecycle performance, setting feasible targets may be a challenge, that may result in frequent changes of the targets or inability to attain the targets.

What-if scenario analysis is an effective tool for setting and evaluating performance targets. Scenario analysis can help identify feasible performance targets under various funding constraints, investigate the impact of alternative investment decisions on these targets, and to determine funding requirements that can realistically achieve and sustain the targets. Figure 24 shows an example of using a scenario to evaluate %Good, %Fair, %Poor performance outcomes and compare against performance targets over a 20-year planning horizon.

The set of optimized asset-specific treatments and treatment bundles identified from what-if scenarios, cross-asset trade-off analysis, needs analysis, and bundling analysis are assembled into project candidates. Project candidates should satisfy both program objectives and funding constraints. However, types and timing of these treatments may not be optimal or practical for project delivery, and therefore additional criteria may need to be considered when project candidates are assembled.



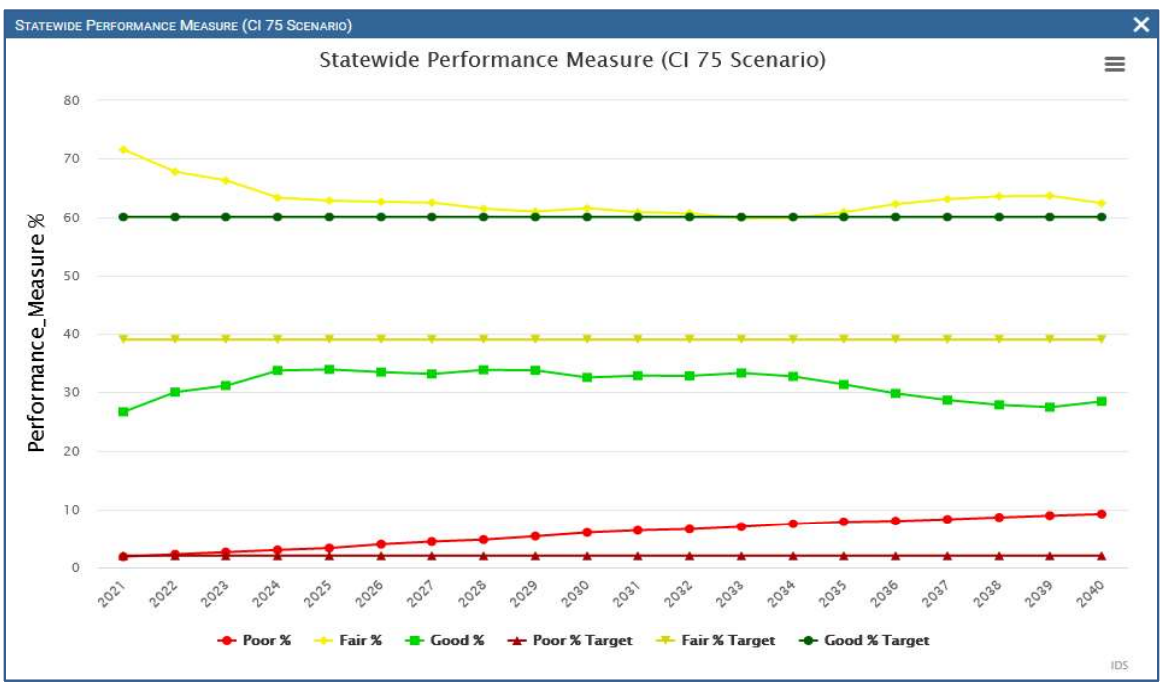


Figure 24: An example of using scenario analysis to compare %Good, %Fair, %Poor performance outcomes against set targets based on a 20-year plan

A project candidate includes one or more treatments, which may span one or more assets and/or asset classes. Candidates may also be added to address specific requirements or risks not addressed by scenarios or identified needs (e.g., for regulatory compliance or coordination). Furthermore, candidates may be added from external management systems (e.g., pavement or bridge management systems).

Each project candidate defines a set of basic attributes such as Project ID, Project Number, location, description, planned year, workflow status, and annual funds allocated from various sources. In addition, a project candidate includes all information pertaining to children work tasks (or treatments) such as work types, estimated costs, list of asset IDs and their associated information, status, allocated funds from different sources, funding commitment years, performance objectives, and expected performance accomplishments, among other attributes. Project costs and other attributes are rolled-up from the costs and attributes of individual treatments.

What-if scenario analysis can also be used to evaluate portfolios of projects or project candidates to accurately determine expected performance outcomes, and provide guidance on adjusting performance targets, or modifying programs and funding allocations to ensure alignment with asset class-specific performance targets and funding constraints.

9.2 MODA-Based Project-Level Trade-off Analysis

Multi-objective decision analysis (MODA) is a popular tool to support project prioritization and selection by assessing the relative benefits of alternative projects. Project benefits are estimated based on a set of performance objectives and associated utility functions. Projects are scored and ranked according to their relative value-to-cost ratios. The MODA approach has the advantage of considering a wide range of asset-generic organizational performance measures (health, safety, efficiency, sustainability, etc.), promoting consistency and transparency in project evaluations, and establishing a quantitative and repeatable process for assessing project benefits.

9.2.1 Caltrans Multi-Objective Decision Analysis (MODA) Model

Caltrans' MODA model prioritizes project candidates based on monetization of project benefits with respect to a set of organizational performance objectives. Figure 25 shows Caltrans' objectives hierarchy based on 2015-2020 Strategic Management Plan, which was used to define MODA objective functions in this study.

In 2016, the SHOPP Asset Management Pilot Program further improved the initial MODA model objectives and value functions, and applied the model to prioritize a set of 37 nominated projects [24]. An Excel-based prototype was also developed to facilitate the use of the model.

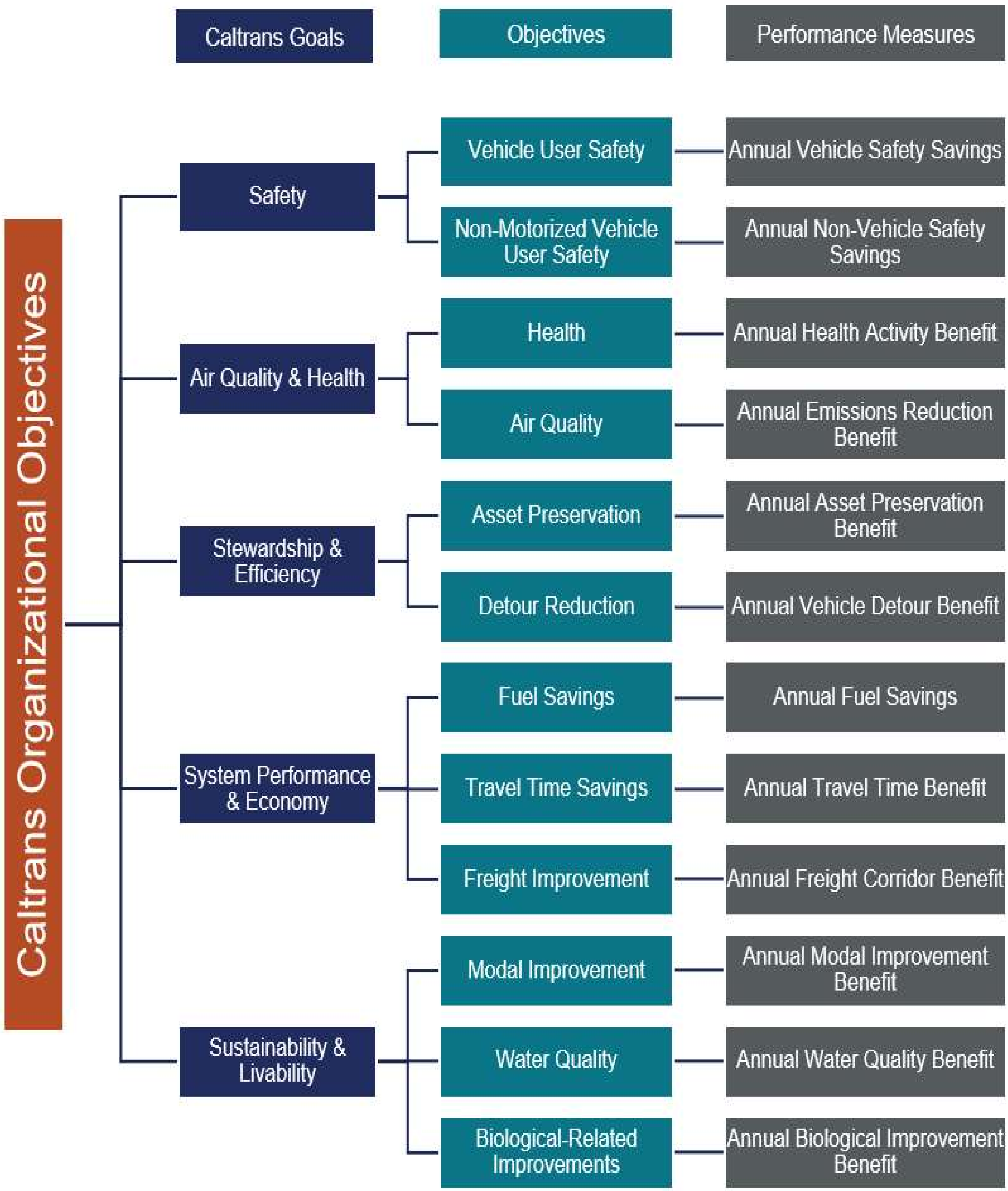


Figure 25: Caltrans MODA Objectives Hierarchy (Based on 2015-2020 Strategic Management Plan)

The MODA model parameters and results from the 2016 project prioritization have been subsequently evaluated by a panel of experts [24], who provided a number of recommendations for possible improvements. Two main recommendations were given:

- Need for further work on how various goals should be weighted and evaluated in the value functions.
- Explore the implementation of an optimization approach to complement the MODA model.

The expert review performed a sensitivity analysis (using the 37 test projects) to assess the impact of changes in input variables (e.g., annual average daily traffic, average annual daily truck traffic, project length, unit costs) on calculated project scores. The sensitivity analysis indicated that significant changes in key input variables have often resulted in small changes in project scores. The review also indicated that some of the value functions may require “a complete overhaul,” and suggested the use of a monetization approach to quantify all project benefits. This finding highlights the difficulty of developing “ideal” value functions to quantify benefits and prioritize statewide capital projects, given the wide range of variations these projects typically have, especially when diverse asset classes are considered. More importantly, this finding also underscores the limitations of relying solely on project-level MODA models for project selections, and the need to utilize true optimization models, similar to the one used in this project.

The expert review investigated the application of two potential optimization approaches to extend the current MODA model, namely a single-objective knapsack optimization (maximize total cumulative project benefit subject to the given budget) and a multi-objective goal programming (maximize benefits for each goal subject to defined goal targets and budget). The two approaches were applied to the same projects data set. However, the two approaches did not yield a significant improvement on the current MODA prioritization results. The study also recommended further work to assist in determining weights and targets of the five different goals, emphasizing the need to develop a multi-objective optimization approach.

Similar to our cross-asset budget allocation method for normalizing cross-asset performance measure (discussed in Section 7.3.1), MODA models also rely on normalizing performance measures for different asset types by defining a set of common utility functions that are applicable across asset types. However, while the MODA approach provides cross-asset project-level trade-off analysis, it does not provide guidance on system-level budget allocation across multiple asset classes.

As a project-level trade-off analysis tool, MODA models are not integrated with predictive performance and risk models and planning scenarios, and therefore, does not allow for analyzing trade-offs and comparing long-term impact of project portfolios on system-level performance measures or to guide decisions among different asset classes or sub-systems. For example, while showing and comparing project-level performance accomplishments, MODA models cannot show the long-term impact of the project portfolio on system-level performance measures (e.g., %Good, %Poor) over the program years. MODA models do not account for project timing and typically evaluate projects value functions at the current planning year, and therefore, do not capture changes in values in subsequent years. Project values that may change due to time-dependent factors, e.g., asset condition, are not captured in the project analysis.

To overcome this limitation, our proposed methodology integrates MODA models with asset and system-level lifecycle modeling, multi-objective cross-asset optimization, and trade-off analysis to optimize the development of project candidates. Under the proposed methodology, project candidates that are evaluated by the MODA model have already been optimized based on asset class-level and system-level trade-off analysis.

9.2.2 Evaluation of Project Candidates using Caltrans MODA Model

Project candidates assembled from optimized scenarios, system-level cross-asset trade-off analysis, and bundling analysis are further evaluated against project-level MODA performance measures to further analyze trade-offs between projects costs and benefits, in terms of organizational performance objectives.

Calculation of MODA value functions for each candidate project requires project and site-specific data attributes that are typically gathered during the project development stage, such as safety statistics, economic benefits, emissions, travel time, health and sustainability benefits. The benefits with respect to each of the defined objectives are evaluated using defined value functions. The total benefits are then calculated and used to calculate a benefit/cost (B/C) ratio score for each project. Projects with the highest B/C ratio are then selected. On each program year, project selection goes from top to bottom until the total annual budget is used. Selected projects are then nominated for programming.

An example for evaluating MODA objectives for some project candidates, a subset of Caltrans MODA goals and objective functions have been defined. Figure 26 shows the definition of three MODA goals as well as the definition of the value functions to estimate system performance benefits, which include: annual freight corridor benefit, annual travel time benefit, and annual fuel savings. While some input variables may be based on readily available asset data (e.g., traffic and truck traffic volume data, VMT), other input variables include a set of statewide or regional constants, such as those provided in Cal B/C including average cost per crash, average fuel cost, and average emissions costs by region. To show the example analysis, assumptions were made for other input variables, which are typically assessed or gathered based on specific site or project parameters.

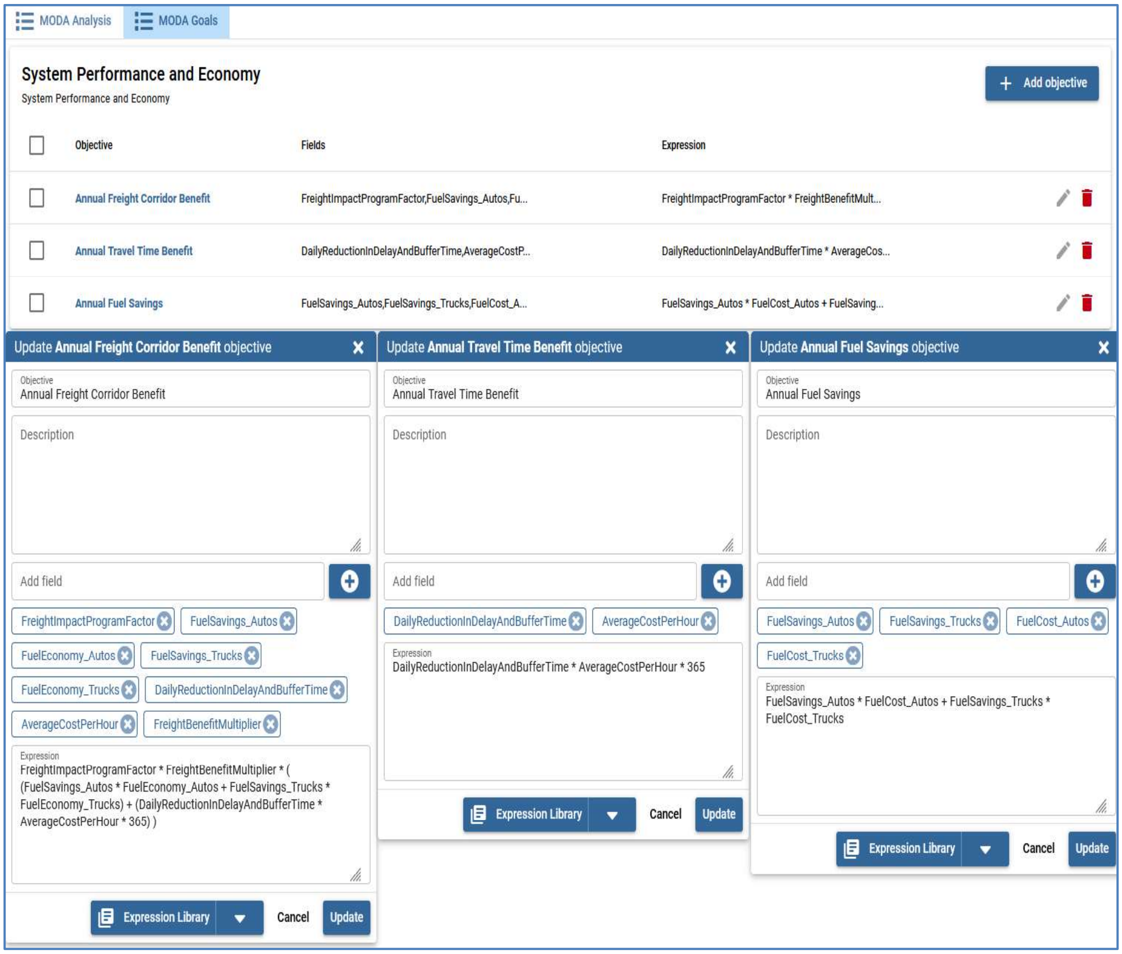


Figure 26: Example of Setting up a Subset of Caltrans MODA Goals and Objective Functions

Figure 27 shows an example for defining project-specific data to estimate value functions under a specific MODA goal. For example, calculation of the annual vehicle safety savings is based on expected annual crash cost savings, using the following formula:

Annual Vehicle User Safety Savings = 365 * VMT * CC * Reduction in Crash Rate

VMT is calculated based on project length (in miles) and AADT, and CC is the average cost per crash ($185,600 based on Cal-B/C). Reduction in crash rate is site-specific and needs to be calculated from existing crash rate (by type of crash) at the project site and expected reduction as a result of the project. In this analysis, this value is assumed to be 0.18 crash per million VMT.

Another example is the calculation of annual fuel savings, which is based on reduced fuel consumption, average fuel economy, and fuel cost for autos and trucks, using the following formula.

Annual Fuel Savings (FS) = $FS_A * C_{AF} + FS_T * C_{TF}$

$$FS_A \text{ (gallon/year)} = EFR_A * 365 * \frac{VMT * \frac{AADT - AADTT}{AADT}}{MPG_A}$$

$$FS_T \text{ (gallon/year)} = EFR_T * 365 * \frac{VMT * \frac{AADTT}{AADT}}{MPG_T}$$

C_{AF} is fuel cost for autos ($2.65/gallon based on Cal-B/C), C_{TF} is fuel cost for trucks ($2.40/gallon based on Cal-B/C), MPG_A is average fuel economy for autos (26.04 miles/gallon based on Cal-B/C), and MPG_T is average fuel economy for trucks (12.18 miles/gallon based on Cal-B/C). EFR_T and EFR_T are effective fuel reduction for autos and trucks. In this analysis, the effective fuel reduction is assumed to be 1% for both autos and trucks.

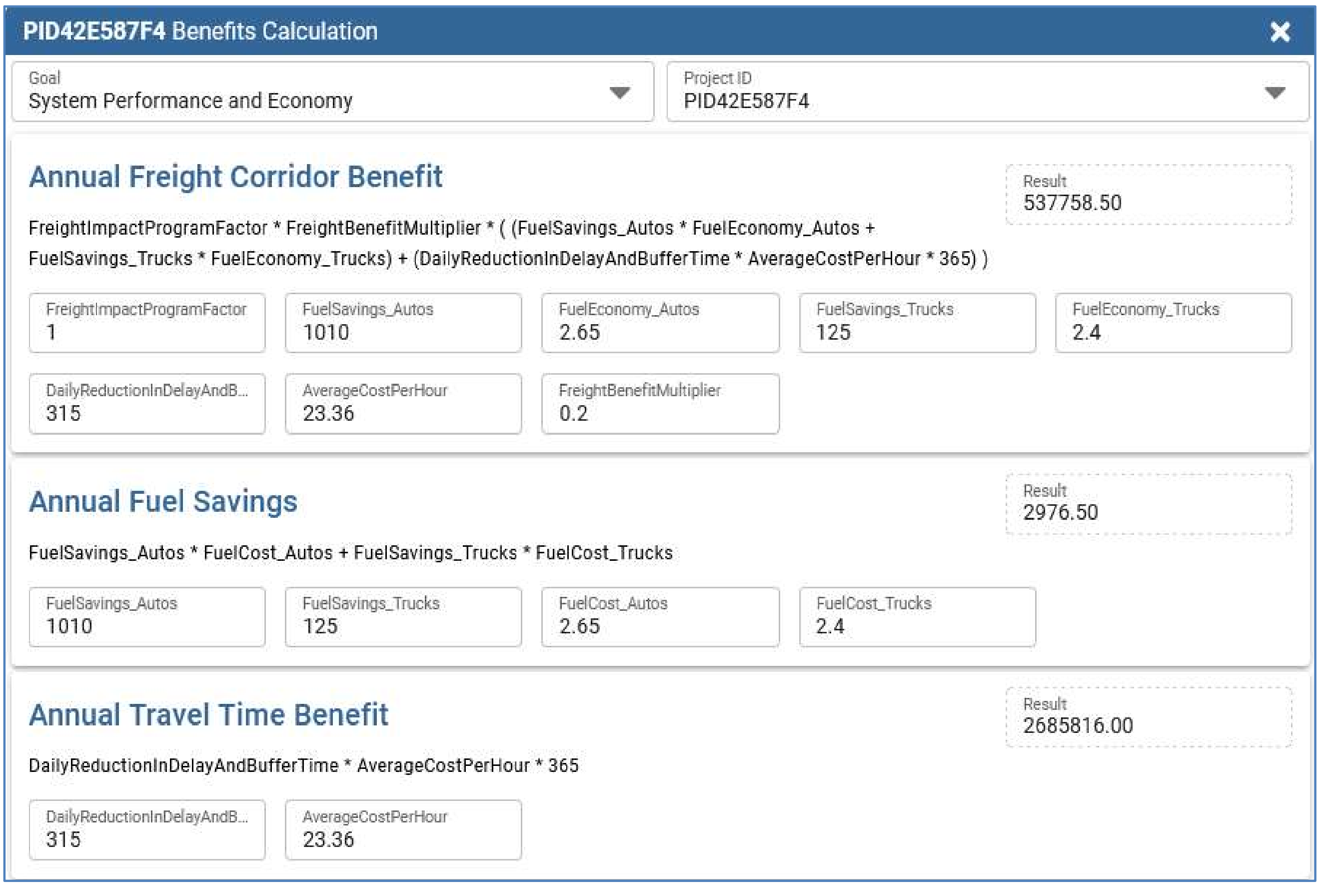


Figure 27: Example input of project parameters for estimating MODA value functions

After defining the project input variables for each value functions, the total benefits of each project are calculated. The MODA project rankings are then calculated based on the benefit-cost ratio. Highest ranking projects within defined funding constraints are then selected and nominated for programming. Figure 28 shows an example of benefits calculations and ranking of project candidates, to be used for nominating projects to programs. Project evaluations and ranking may be modified as a result of adjusting project parameters (e.g., scope, timing, etc.). Furthermore, identified or nominated candidates may be evaluated using scenario analysis to verify that system-level performance objectives will be still met over the duration of the program.

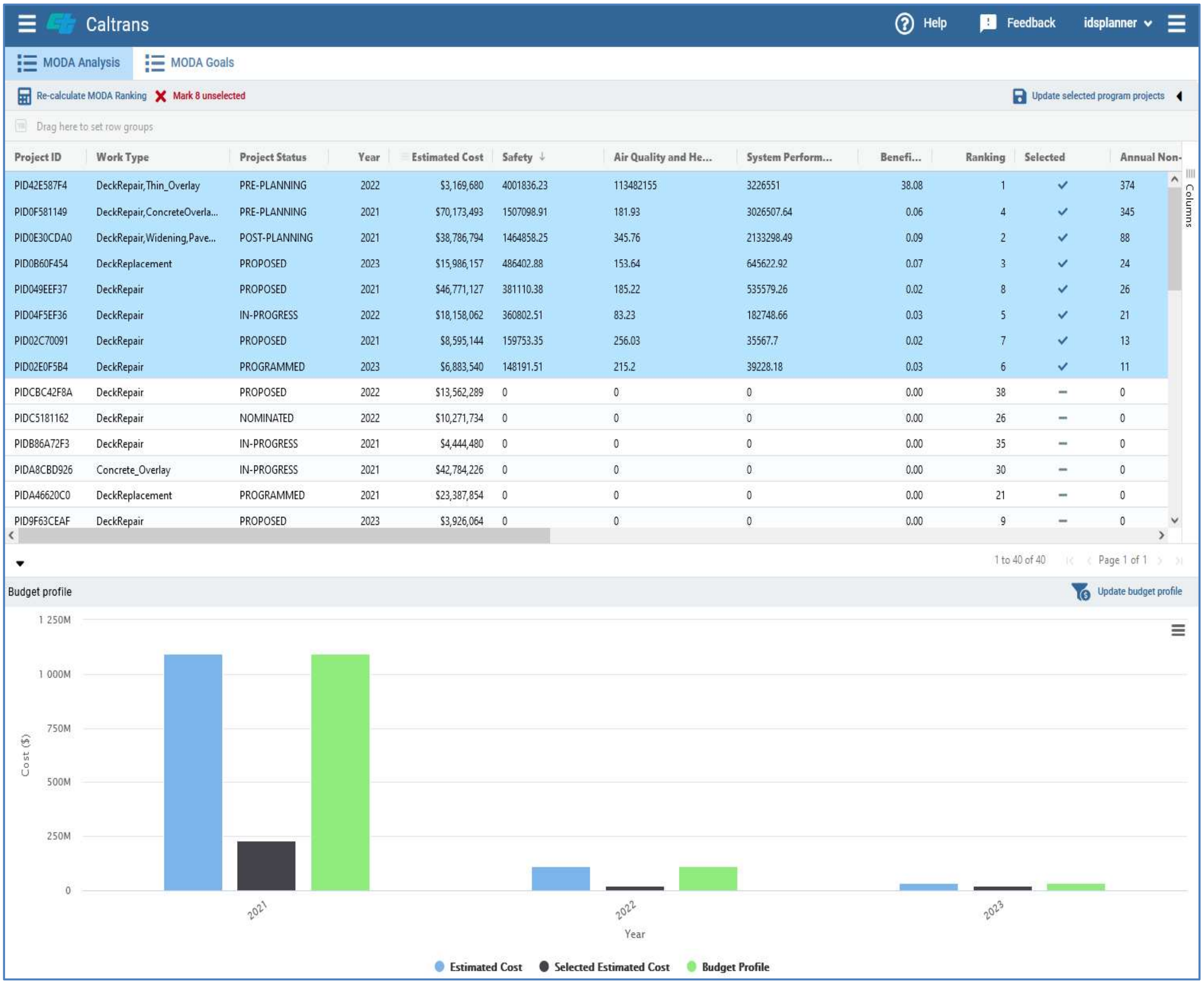
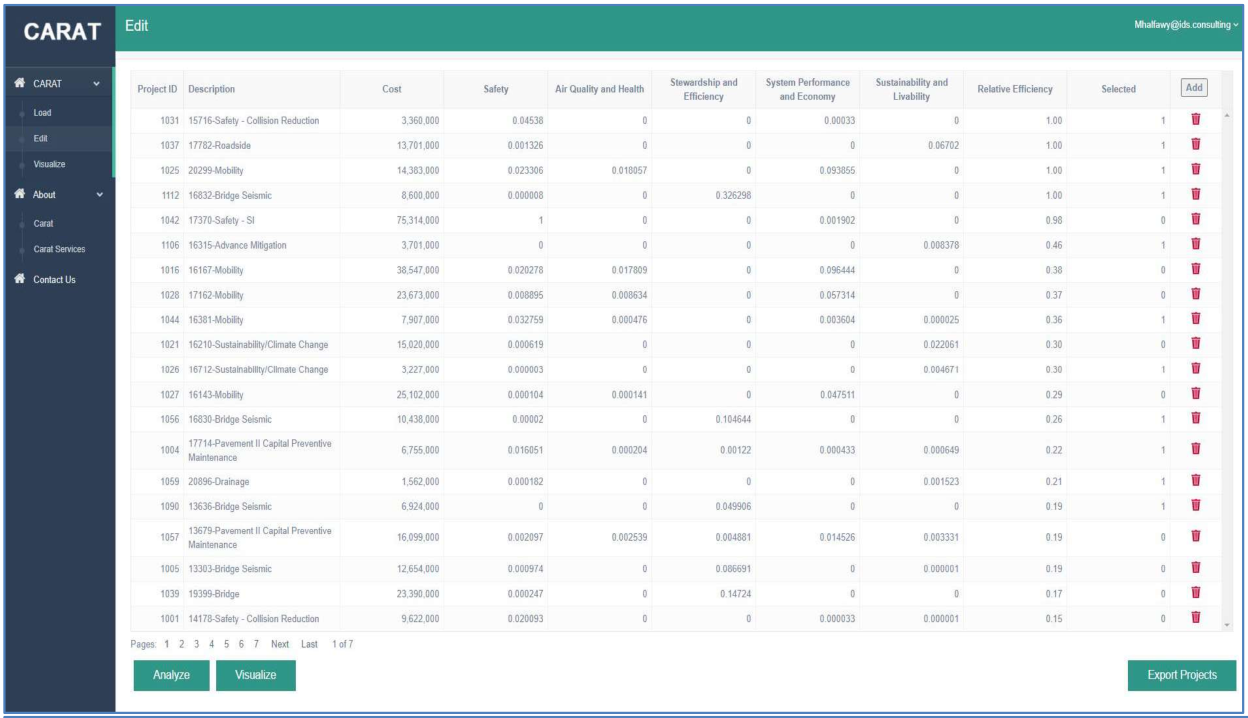


Figure 28: Ranking project candidates based on B/C ratio and nominating highest value projects for programming. Highest-Value Candidate Projects for Program Nomination

We initially used the Cross-Asset Resource Allocation Tool (CARAT) web service [25] to perform MODA analysis. The CARAT REST service was integrated with Asset Optimizer to automate data exchange and MODA ranking. Developed as part of the NCHRP 08-91 project, the CARAT tool employs Data Envelopment Analysis (DEA) to calculate a relative efficiency for each project, which is subsequently used to rank projects based on benefit values. For testing purposes, we used the CARAT tool to analyze a small set of projects (Figure 29).



Project ID	Description	Cost	Safety	Air Quality and Health	Stewardship and Efficiency	System Performance and Economy	Sustainability and Livability	Relative Efficiency	Selected
1031	15716-Safety - Collision Reduction	3,360,000	0.04538	0	0	0.00033	0	1.00	1
1037	17782-Roadside	13,701,000	0.001326	0	0	0	0.06702	1.00	1
1025	20299-Mobility	14,383,000	0.023306	0.018057	0	0.093855	0	1.00	1
1112	16832-Bridge Seismic	8,600,000	0.000008	0	0.326298	0	0	1.00	1
1042	17370-Safety - SI	75,314,000	1	0	0	0.001902	0	0.98	0
1106	16315-Advance Mitigation	3,701,000	0	0	0	0	0.008378	0.46	1
1016	16167-Mobility	38,547,000	0.020278	0.017809	0	0.096444	0	0.38	0
1028	17162-Mobility	23,673,000	0.008895	0.008634	0	0.057314	0	0.37	0
1044	16381-Mobility	7,907,000	0.032759	0.000476	0	0.003604	0.000025	0.36	1
1021	16210-Sustainability/Climate Change	15,020,000	0.000619	0	0	0	0.022061	0.30	0
1026	16712-Sustainability/Climate Change	3,227,000	0.000003	0	0	0	0.004671	0.30	1
1027	16143-Mobility	25,102,000	0.000104	0.000141	0	0.047511	0	0.29	0
1056	16830-Bridge Seismic	10,438,000	0.00002	0	0.104644	0	0	0.26	1
1004	17714-Pavement II Capital Preventive Maintenance	6,755,000	0.016051	0.000204	0.00122	0.000433	0.000649	0.22	1
1059	20896-Drainage	1,562,000	0.000182	0	0	0	0.001523	0.21	1
1090	13636-Bridge Seismic	6,924,000	0	0	0.049906	0	0	0.19	1
1057	13679-Pavement II Capital Preventive Maintenance	16,099,000	0.002097	0.002539	0.004881	0.014526	0.003331	0.19	0
1005	13303-Bridge Seismic	12,654,000	0.000974	0	0.086691	0	0.000001	0.19	0
1039	19399-Bridge	23,390,000	0.000247	0	0.14724	0	0	0.17	0
1001	14178-Safety - Collision Reduction	9,622,000	0.020093	0	0	0.000033	0.000001	0.15	0

Project ID	Description	Efficiency	Cost
1003	16628-Pavement-II-Capital-Preventive-Maintenance	0.12	2,704,000
1004	17714-Pavement-II-Capital-Preventive-Maintenance	0.22	6,755,000
1007	13838-Roadside	0.13	2,590,000
1025	20299-Mobility	1.00	14,383,000
1026	16712-Sustainability-Climate-Change	0.30	3,227,000
1031	15716-Safety-Collision-Reduction	1.00	3,360,000
1037	17782-Roadside	1.00	13,701,000
1041	16240-Mobility	0.10	4,484,000
1044	16381-Mobility	0.36	7,907,000
1056	16830-Bridge-Seismic	0.26	10,438,000
1059	20896-Drainage	0.21	1,562,000
1090	13636-Bridge-Seismic	0.19	6,924,000
1106	16315-Advance-Mitigation	0.46	3
1112	16832-Bridge-Seismic	1.00	8,600,000
1114	18351-Other	0.09	2,165,000

Figure 29: Example use of the CARAT Service for a Small Set of Projects

Experiments with the CARAT service showed some scalability limitations. The tool performed well when the number of projects was in the range of 300. However, we experienced some limitations when a larger number of candidate projects (e.g., in a 10-year program) were evaluated. To overcome this limitation, we decided to implement MODA calculations and ranking using benefit-cost ratio in the Asset Optimizer tool, instead of using CARAT service.

9.3 Managing and Tracking of Programs and Budgets

Funding for programs and projects are typically allocated from multiple sources, over the program years, within certain limits and according to specific rules. Prior to allocating funds, funding sources should be set up with their available annual limits. Figure 30 shows an example of setting up a funding source, and defining program annual funding allocation.

As multiple funds can be allocated to multiple programs over different years, continuous tracking and management of funds as they are allocated, deallocated, rolled-over, or consumed over programs' lifecycle can become a complex task. Fund consumption are typically tracked through recording of actual project costs, which is typically achieved using a project management system. At any point in time, allocated, remaining, and consumed funds should be balanced across all programs and funding sources. Figure 31 shows an example of a program summary, and annual funding allocations from multiple sources to different projects.

Different programs may require different workflow processes to streamline program execution and determine the requirements for developing and advancing projects through their lifecycle. Advancement of projects status across different stages from nomination, to pre-planning, planning, post-planning, programming, and delivery stages typically involves a series of submission and approval processes. Each of these processes would typically have a set of prerequisites and documentation, and trigger specific actions, notifications, or changes in project status. Figure 32 shows an example of a generic program workflow.

Throughout the program lifecycle, it is critical to monitor and track projects delivery to ensure alignment with performance and budget expectation. Deviations from initial performance and funding forecasts are common occurrences in projects, and therefore the need for program adjustments and updates often arises due to new or unforeseen aspects of actual expenditures, asset needs, funding constraints, or compliance requirements. Figure 33 shows an example program management interface showing the project portfolio and details of a selected project, which include the list of tasks (treatments), allocated funds, and workflow status.

Program changes may trigger the need to re-evaluate the project portfolio, which may result in adding, removing, or swapping projects to meet performance and funding constraints. Ideally, project updates should be automatically synchronized between the program management and project management systems to reflect project updates in real-time throughout the delivery lifecycle, which allows for timely decisions on any required adjustments as well as accurate reporting on program status. Figure 34 shows an example of a program status dashboard, showing fund allocation, cost estimates, and actual expenditures.

Federal Fund

Add funds | Rollover funds | Allocate program funds

Total Amount	Allocated	Remaining
$8,870,000,250	$856,500,000	$8,013,500,250

Year	Annual Source Total	Allocated Annual Total	Unallocated Annual Total
2021	$989,999,200	$105,000,050	$884,999,150
2022	$760,001,050	$105,999,950	$654,001,100
2023	$793,000,000	$103,000,000	$690,000,000
2024	$750,500,000	$106,000,000	$644,500,000
2025	$906,000,000	$96,000,000	$810,000,000
2026	$1,100,500,000	$90,500,000	$1,010,000,000
2027	$1,000,000,000	$75,000,000	$925,000,000
2028	$900,000,000	$75,000,000	$825,000,000
2029	$900,000,000	$50,000,000	$850,000,000
2030	$770,000,000	$50,000,000	$720,000,000
Total	$8,870,000,250	$856,500,000	$8,013,500,250

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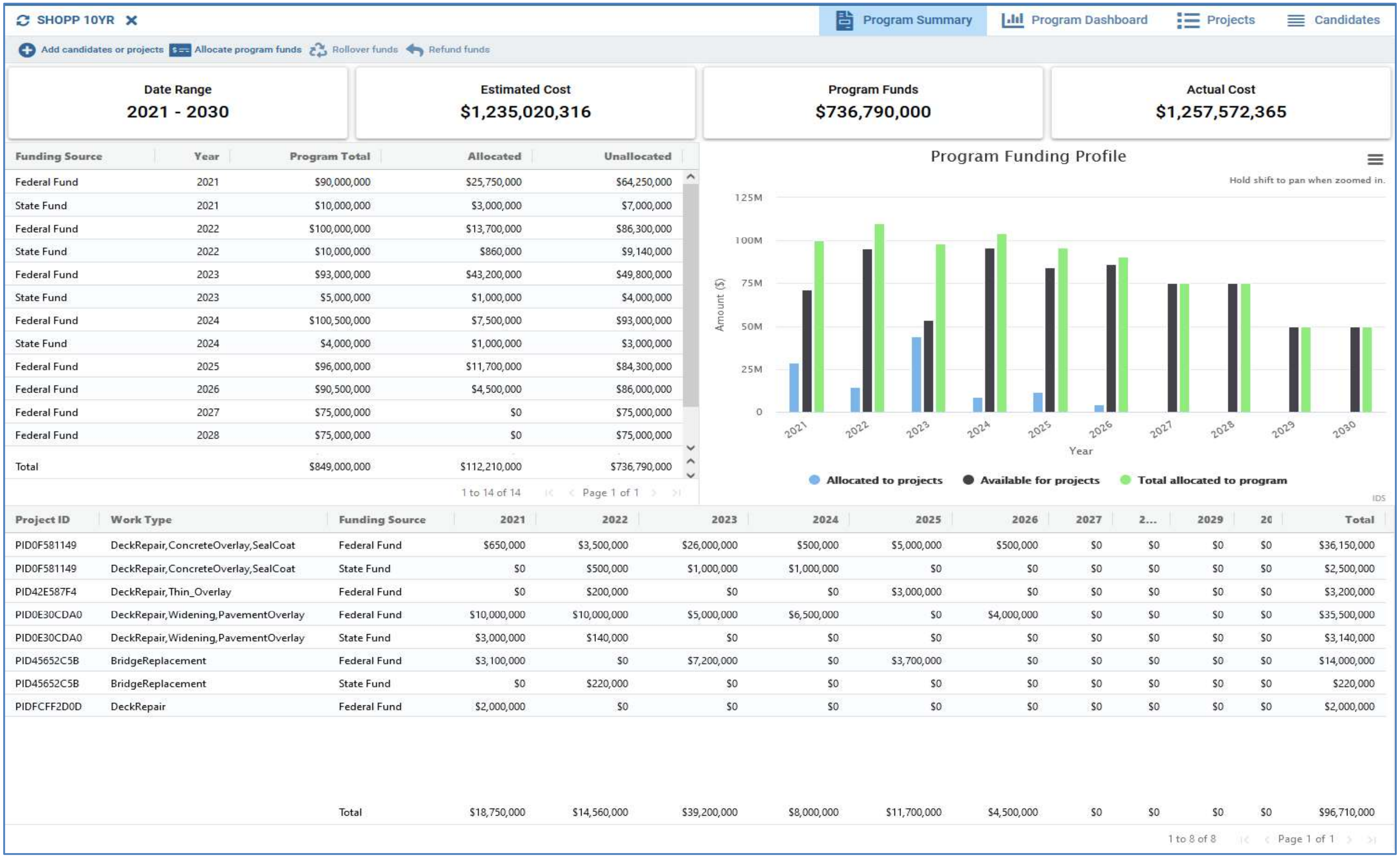
Program	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030	Total
D4 Program	$5,000,050	$5,999,950	$5,000,000	$5,000,000	$0	$0	$0	$0	$0	$0	$21,000,000
SHOPP 10YR	$90,000,000	$100,000,000	$93,000,000	$100,500,000	$96,000,000	$90,500,000	$75,000,000	$75,000,000	$50,000,000	$50,000,000	$820,000,000
Total	$95,000,050	$105,999,950	$98,000,000	$105,500,000	$96,000,000	$90,500,000	$75,000,000	$75,000,000	$50,000,000	$50,000,000	$841,000,000

1 to 2 of 2 Page 1 of 1

Figure 30: An example of setting up a funding source in the example program



Funding Source	Year	Program Total	Allocated	Unallocated
Federal Fund	2021	$90,000,000	$25,750,000	$64,250,000
State Fund	2021	$10,000,000	$3,000,000	$7,000,000
Federal Fund	2022	$100,000,000	$13,700,000	$86,300,000
State Fund	2022	$10,000,000	$860,000	$9,140,000
Federal Fund	2023	$93,000,000	$43,200,000	$49,800,000
State Fund	2023	$5,000,000	$1,000,000	$4,000,000
Federal Fund	2024	$100,500,000	$7,500,000	$93,000,000
State Fund	2024	$4,000,000	$1,000,000	$3,000,000
Federal Fund	2025	$96,000,000	$11,700,000	$84,300,000
Federal Fund	2026	$90,500,000	$4,500,000	$86,000,000
Federal Fund	2027	$75,000,000	$0	$75,000,000
Federal Fund	2028	$75,000,000	$0	$75,000,000
Total		$849,000,000	$112,210,000	$736,790,000

Project ID	Work Type	Funding Source	2021	2022	2023	2024	2025	2026	2027	2...	2029	20	Total
PID0F581149	DeckRepair,ConcreteOverlay,SealCoat	Federal Fund	$650,000	$3,500,000	$26,000,000	$500,000	$5,000,000	$500,000	$0	$0	$0	$0	$36,150,000
PID0F581149	DeckRepair,ConcreteOverlay,SealCoat	State Fund	$0	$500,000	$1,000,000	$1,000,000	$0	$0	$0	$0	$0	$0	$2,500,000
PID42E587F4	DeckRepair,Thin_Overlay	Federal Fund	$0	$200,000	$0	$0	$3,000,000	$0	$0	$0	$0	$0	$3,200,000
PID0E30CDA0	DeckRepair,Widening,PavementOverlay	Federal Fund	$10,000,000	$10,000,000	$5,000,000	$6,500,000	$0	$4,000,000	$0	$0	$0	$0	$35,500,000
PID0E30CDA0	DeckRepair,Widening,PavementOverlay	State Fund	$3,000,000	$140,000	$0	$0	$0	$0	$0	$0	$0	$0	$3,140,000
PID45652C5B	BridgeReplacement	Federal Fund	$3,100,000	$0	$7,200,000	$0	$3,700,000	$0	$0	$0	$0	$0	$14,000,000
PID45652C5B	BridgeReplacement	State Fund	$0	$220,000	$0	$0	$0	$0	$0	$0	$0	$0	$220,000
PIDFCFF2D0D	DeckRepair	Federal Fund	$2,000,000	$0	$0	$0	$0	$0	$0	$0	$0	$0	$2,000,000
		Total	$18,750,000	$14,560,000	$39,200,000	$8,000,000	$11,700,000	$4,500,000	$0	$0	$0	$0	$96,710,000

Figure 31: Example program summary of fund allocations from multiple sources to different projects.

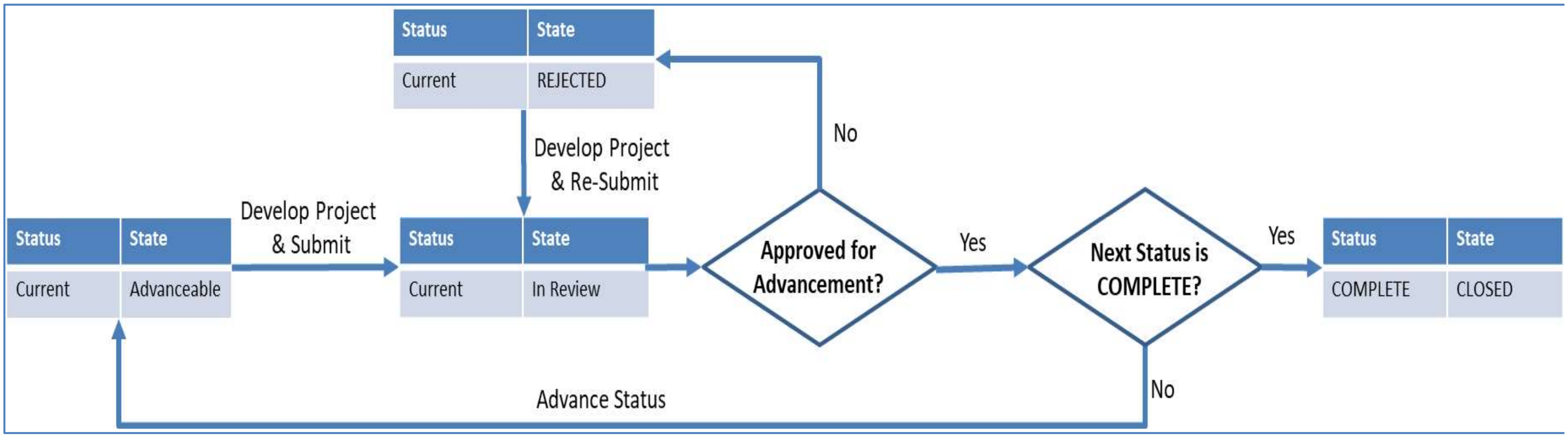


Figure 32: An example of a generic program workflow for project advancement

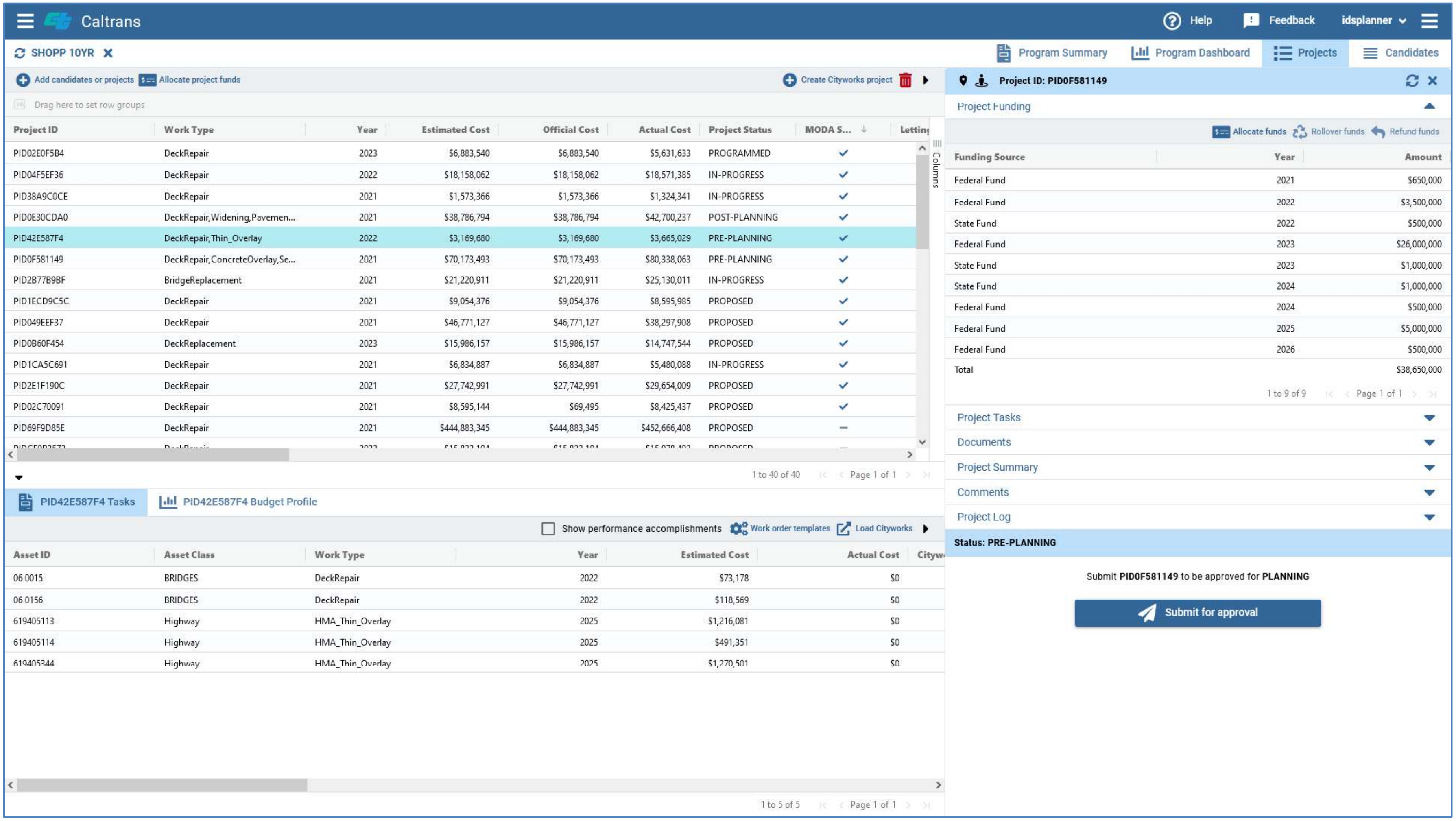


Figure 33: An example project portfolio showing details of a specific project including the list of tasks (treatments), allocated funds, and workflow status.

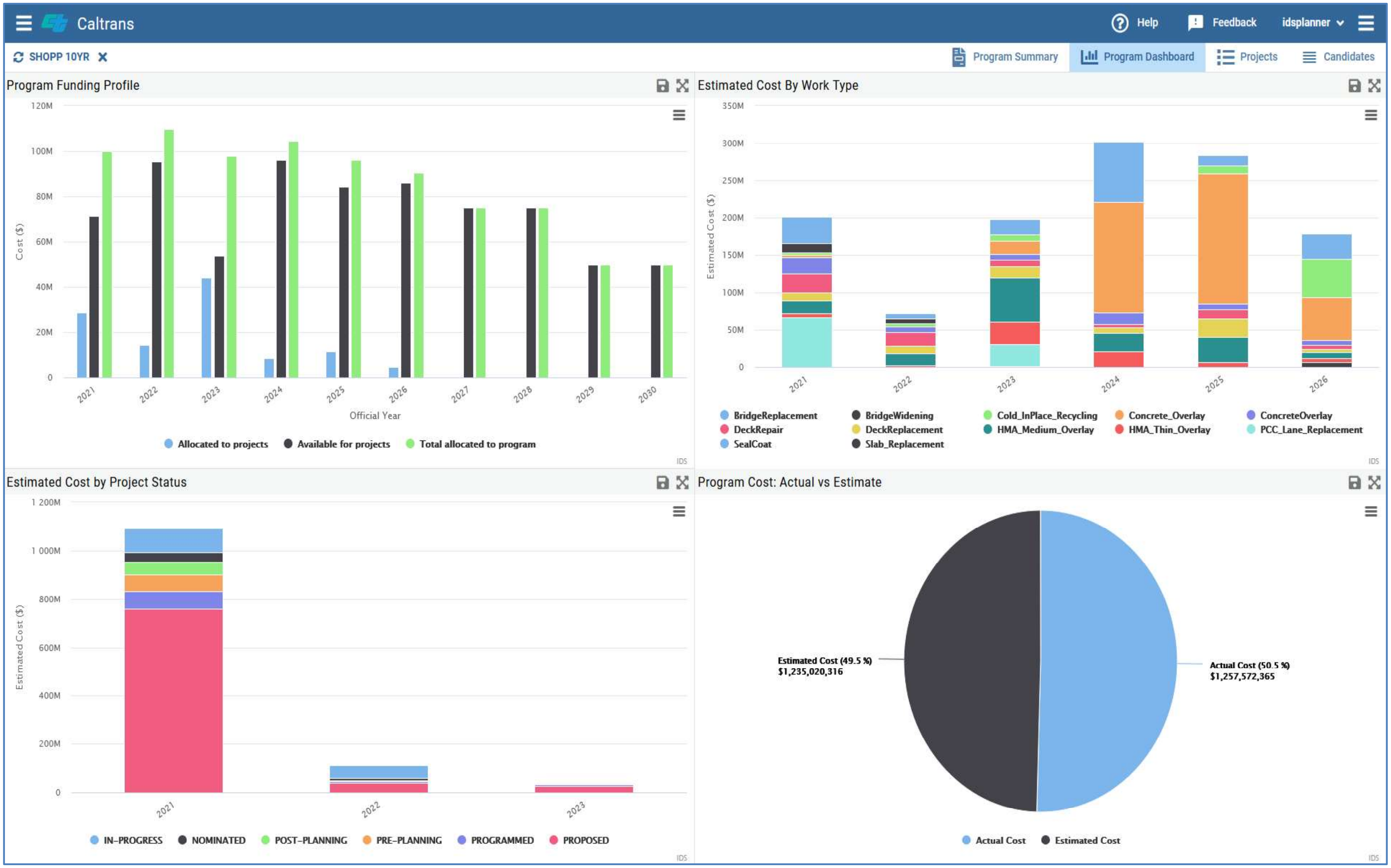


Figure 34: Example summary program status showing annual allocated funds, estimated costs, and actual expenditures.

What-if scenario analysis can be used for evaluating and predicting asset class-specific performance measures of a given project portfolios based on predictive performance models. The impact of changes in project statuses during program delivery phases can be evaluated, along with analyzing trade-offs of possible adjustments that can be introduced to ensure alignment with performance targets and funding constraints. Based on this analysis, program and project adjustments can be made and justified.

10 Comparison of Analysis Results and SHOPP Projects

In an attempt to compare the results of the proposed methodology against the actual SHOPP projects, a review of Caltrans SHOPP projects was undertaken. Appendix C includes a spreadsheet showing comparison of SHOPP projects and the results of planning scenarios simulating SHOPP 10-year investment levels for SHS bridges and pavements. To compare bridge projects, Caltrans bridge needs spreadsheet (updated on October 2019) and the official 2020 SHOPP project list were reviewed (Figure 35). Figure 36 shows a map of the bridge needs and SHOPP projects.

Bridge needs included 6,252 projects in total, with 1,369 records having associated SHOPP Tool ID values. The records were joined with corresponding projects in the official 2020 SHOPP project list using common SHOPP Tool ID. Approximately 711 needs projects had matching SHOPP IDs in the official plan. The resulting records were subsequently joined with the scenario result from SHOPP 10-years scenario (2021-2030) using bridge structure numbers as a common key. The SHOPP 10-year scenario assumed the same 4-year budget of the SHOPP program ($722 million, $766 million, $452 million, $551 million), and then assumed a constant budget of $551 million for the remaining years.

The SHOPP 10-year planning scenario has approximately 198 bridge projects related to the SHOPP projects, mostly related to e.g., Bridge health, deck rehab, deck methacrylate treatments. However, the treatments definition and cost estimates varied widely between the recommended projects and official projects. The treatment types considered in the optimization scenario aligned with only a small subset of the treatments defined in the needs sheet. While the optimization algorithm considered six main treatments (bridge replacement, deck replacement, deck repair, concrete overlay, bridge widening, and prestressed beam end repair), the needs project list included several treatments that are not considered in the scenario, such as railing repair/upgrade, seismic retrofit, scour mitigation, substructure and superstructure rehabilitation, etc.

	BrEA from SMI	Bridge Found	BridgeNo	SHOPP tool ID	Dist	EFIS ID	EA	County	Route	Begin	End PM	Main Activity Category	Advertisem	Construction Con	Funding Sou	SMI Health P	DKRATING	SUPRATING	SUBRATING	CULVRATIN(	SMI Scour P	SCOURCRIT	SMI Seism	SMI GM Pr	SMI Rail Pre Con	Health Post-Condi	Scour P
2	01 00030B090	01 0003	01 0003	13126	1	100020444	0B090	Del Norte	101	8.2	8.7	Bridge	2019	44825.7375	SHOPP	Good	8	8	8	N	Fair	4	Poor	Good	Good	Good	Good
3	01 00040F400	01 0004	01 0004	N/A	1	116000007	0F400	HUM	VAR			HM3	2017	43104	HM	Good	8	8	8	N	Good	8	Good	Good	Good	Good	Good
4	01 00060J860	01 0006	01 0006	N/A	1	119000116	0J860	DN	199			HM3 SHA	2021	45231	HM	Good	7	7	7	N	Good	8	Good	Good	Good	Good	Good
5	01 00090J860	01 0009	01 0009	N/A	1	119000116	0J860	DN	199			HM3 SHA	2021	45231	HM	Fair	5	7	7	N	Fair	5	Good	Good	Good	Good	Fair
6	01 00160J860	01 0016	01 0016	N/A	1	119000116	0J860	DN	199			HM3 SHA	2021	45231	HM	Fair	5	7	7	N	Good	8	Good	Good	Good	Good	Good
7	01 00200J180	01 0020	01 0020	N/A	1	118000186	0J180	HUM	VAR			HM3 SB1	2020	44501	HM	Fair	7	7	5	N	Poor	3	Good	Poor	Poor	Fair	Poor
8	01 002043640	01 0020	01 0020	9014	1	100000193	43640	Del Norte	101	36.1	0	Bridge - Health	2021	45933.70833	SHOPP	Good	8	7	7	N	Poor	3	Good	Poor	Poor	Good	Good
9	01 00230A100	01 0023	01 0023	N/A	1	112000023	0A100	DN	101	35.8	35.77	20.XX.201.113	2016	42983.70833	SHOPP	Good	7	7	8	N	Fair	5	Poor	Fair	Good	Good	Fair
10	01 00230J860	01 0023	01 0023	N/A	1	119000116	0J860	DN	199			HM3 SHA	2021	45231	HM	Good	7	7	7	N	Fair	5	Good	Fair	Good	Good	Fair
11	01 00250B090	01 0025	01 0025	13126	1	100020444	0B090	Del Norte	101	8.2	8.7	Bridge	2019	44825.7375	SHOPP	Good	8	8	8	N	Good	8	Poor	Good	Fair	Good	Good
12	01 00460A100	01 0046	01 0046	N/A	1	112000023	0A100	DN	101	35.8	35.77	20.XX.201.113	2016	42983.70833	SHOPP	Good	8	8	7	N	Fair	5	Poor	Good	Good	Good	Fair
13	01 0058F0A100	01 0058F	01 0058F	N/A	1	112000023	0A100	DN	101	35.8	35.77	20.XX.201.113	2016	42983.70833	SHOPP	Good	8	8	8	N	N/A	N	Poor	Good	Fair	Good	N/A
14	01 00630A100	01 0063	01 0063	N/A	1	112000023	0A100	DN	101	35.8	35.77	20.XX.201.113	2016	42983.70833	SHOPP	Good	8	8	8	N	N/A	N	Poor	Good	Good	Good	N/A
15	01 00790F400	01 0079	01 0079	N/A	1	116000007	0F400	HUM	VAR			HM3	2017	43104	HM	Good	7	8	8	N	N/A	N	Good	Good	Good	Good	N/A
16	02 00024H130	02 0002	02 0002	N/A	2	218000134	4H130	SHA	VAR			HM3 SHA	2020	44105	HM	Good	7	7	7	N	Fair	5	Good	Good	Good	Good	Fair
17	02 00021H480	02 0002	02 0002	14182	2	216000019	1H480	Siskiyou	5	2.5	3	Bridge - Health	2022	46022.70833	SHOPP	Good	7	7	7	N	Fair	5	Good	Good	Good	Good	Fair
18	02 0004L4F540	02 0004L	02 0004L	11244	2	213000004	4F540	Siskiyou	5	R15.3	R16.5	Bridge - Health	2018	44575.70833	SHOPP	Fair	6	7	6	N	N/A	N	Good	Good	Fair	Good	N/A
19	02 0004R1H950	02 0004R	02 0004R	N/A	2	216000159	1H950	SIS	Var	Var	Var	HM3	2018	43413	HM	Fair	8	7	6	N	N/A	N	Good	Good	Fair	Fair	N/A
20	02 0004R4F540	02 0004R	02 0004R	11244	2	213000004	4F540	Siskiyou	5	R15.3	R16.5	Bridge - Health	2018	44575.70833	SHOPP	Fair	8	7	6	N	N/A	N	Good	Good	Fair	Fair	N/A
21	02 00152E480	02 0015	02 0015	11161	2	200000586	2E480	Siskiyou	263	56.8	57.2	Bridge - Health	2018	44515.70833	SHOPP	Fair	8	6	7	N	Fair	5	Poor	Good	Good	Good	Good
22	02 00224F600	02 0022	02 0022	9269	2	213000012	4F600	Trinity	299	0	0	Bridge - Health	2020	44845.70833	SHOPP	Good	7	8	7	N	Fair	5	Good	Good	Fair	Good	Fair
23	02 00274F600	02 0027	02 0027	9269	2	213000012	4F600	Trinity	299	0	0	Bridge - Health	2020	44845.70833	SHOPP	Fair	8	8	6	N	Good	8	Good	Good	Fair	Fair	Good
24	02 0032L4G240	02 0032L	02 0032L	N/A	2	213000095	4G240	SIS	005	24.9	25.59	20.XX.201.322	2017	44119.70833	SHOPP	Good	7	8	7	N	N/A	N	Good	Good	Fair	Good	N/A
25	02 0032R4G240	02 0032R	02 0032R	N/A	2	213000095	4G240	SIS	005	24.9	25.59	20.XX.201.322	2017	44119.70833	SHOPP	Good	7	8	7	N	N/A	N	Good	Good	Fair	Good	N/A
26	02 0036R3H320	02 0036R	02 0036R	16682	2	217000097	3H320	Siskiyou	5	2.7	R15.9	Pavement	2022	46342.70833	SHOPP	Good	7	7	7	N	N/A	N	Good	Good	Fair	Good	N/A
27	02 00424G440	02 0042	02 0042	16609	2	214000013	4G440	Siskiyou	3	38	38.6	Bridge - Health	2021	44573.70833	SHOPP	Fair	5	7	8	N	Good	8	Good	Good	Good	Good	Good
28	02 00441H950	02 0044	02 0044	N/A	2	216000159	1H950	SIS	Var	Var	Var	HM3	2018	43413	HM	Good	8	8	7	N	Good	8	Good	Good	Good	Good	Good
29	02 00464F550	02 0046	02 0046	11245	2	213000005	4F550	Siskiyou	89	20.9	21.2	Bridge - Health	2018	43453	SHOPP	Poor	4	7	5	N	Good	8	Good	Good	Good	Good	Good
30	02 00652H080	02 0065	02 0065		2	216000096	2H080	SHA				HM3	2016	42458	HM	Fair	8	8	7	N	N/A	N	Good	Good	Good	Fair	N/A
31	02 00661H950	02 0066	02 0066	N/A	2	216000159	1H950	SIS	Var	Var	Var	HM3	2018	43413	HM	Good	7	8	7	N	N/A	N	Good	Good	Good	Good	N/A

	SHOPP ID	District	County	Route	Begin Mile	End Mile	Activity	Planning_or_Post	Adertised Year	Cost	SB1_Priority
2	20275	1	Del Norte	101	0	46.5	Drainage	Planning	2026_27		Yes
3	22305	1	Del Norte	101	8.2	8.7	Bridge	Post-Planning	2021_22	438	Yes
4	16494	1	Del Norte	101	12	15.5	Major Damage - Permane	Post-Planning	2030_31	10075	
5	21946	1	Del Norte	101	12.6	13.2	Major Damage - Permane	Planning	2023_24		
6	17537	1	Del Norte	101	21.2		Major Damage - Permane	Post-Planning	2020_21	18227	
7	16236	1	Del Norte	101	25.6	27.3	Mobility - ADA	Post-Planning	2019_20	10157	
8	21446	1	Del Norte	101	31.2	39.6	Safety Improvements	Planning	2021_22		
9	9014	1	Del Norte	101	35.8	36.5	Bridge	Post-Planning	2020_21	84989	Yes
10	16887	1	Del Norte	101	39.8		Bridge	Post-Planning	2019_20	10009	Yes
11	20247	1	Del Norte	101	R3.9	23.6	Pavement	Post-Planning	2024_25	42560	Yes
12	16414	1	Del Norte	101	R5.1	R5.6	Mobility - Operational Im	Post-Planning	2021_22	4235	
13	21413	1	Del Norte	199	1.1	2.6	Drainage	Post-Planning	2020_21	3910	Yes
14	21401	1	Del Norte	199	6.3	36.3	Drainage	Post-Planning	2019_20	5092	Yes
15	17515	1	Del Norte	199	10.2	10.7	Safety Improvements	Post-Planning	2019_20	2990	
16	21687	1	Del Norte	199	22.07	36.408	Pavement	Planning	2026_27		Yes
17	21751	1	Del Norte	199	27.2	27.6	Safety Improvements	Planning	2022_23		
18	16443	1	Del Norte	199	28.1		Facilities	Post-Planning	2021_22	8187	
19	21845	1	Del Norte	199	33.5	33.9	Major Damage - Emergen	Post-Planning	2019_20	6220	
20	16424	1	Del Norte	199	33.5	33.9	Safety	Post-Planning	2020_21	4685	
21	20286	1	Humboldt	36	0	45.5	Drainage	Planning	2027_28		Yes
22	13533	1	Humboldt	36	0.1	1.6	Safety - Collision Reducti	Post-Planning	2020_21	13878	
23	21406	1	Humboldt	36	3	6	Safety Improvements	Planning	2021_22		

V4.0 2020 SHOPP Project List
Alameda
($1,000)

Caltrans

Dist-Co-Rte Post Mile PPNO Project ID	Location/Description	EA Prog Year	Capital	Support	COS Allocation FY	Milestones
04-Alameda-84 17.0/17.4 0481M 0414000012 Carryover	Near Sunol, at Arroyo De La Laguna Bridge No. 33-0043. Replace/rehabilitate bridge for scour mitigation, bridge rail upgrade and seismic retrofit.	0J550 2021-22	R/W: $500 Con: $13,000 Subtotal: $13,500 Total Project Cost:	PA&ED: $1,863 PS&E: $3,600 R/W Sup: $250 Con Sup: $3,600 $9,313 $22,813	Prior Prior Prior 21-22	PA&ED: 10/1/2020 R/W Cert: 3/1/2022 RTL: 4/1/2022 Begin Con: 11/30/2022

Program 201.111 Bridge Scour Mitigation
Project Output(s) 1 Bridge(s)

Primary Asset (Scour)	Good	Fair	Poor	Quantity	Unit
Existing Condition	0.0	0.0	11,776.0	11,776.0	Square feet
Post Condition	22,010.0	0.0	0.0	22,010.0	Square feet

Bridge Health	Existing Condition	Post Condition
Bridge No. 33-0043	Good	Good

Dist-Co-Rte Post Mile PPNO Project ID	Location/Description	EA Prog Year	Capital	Support	COS Allocation FY	Milestones
04-Alameda-680 R10.2 20208 0418000025 New	Near Sunol, at Alameda Creek Bridge No. 33-0047. Scour mitigation, bridge deck rehabilitation, and joint seal replacement.	0P910 2023-24	R/W: $305 Con: $7,461 Subtotal: $7,766 Total Project Cost:	PA&ED: $1,699 PS&E: $1,602 R/W Sup: $223 Con Sup: $2,166 $5,690 $13,456	20-21 22-23 22-23 23-24	PA&ED: 7/1/2022 R/W Cert: 2/1/2024 RTL: 3/1/2024 Begin Con: 10/1/2024

Program 201.111 Bridge Scour Mitigation
Project Output(s) 1 Bridge(s)

Primary Asset (Scour)	Good	Fair	Poor	Quantity	Unit
Existing Condition	0.0	0.0	79,857.0	79,857.0	Square feet
Post Condition	79,857.0	0.0	0.0	79,857.0	Square feet

Bridge Health	Existing Condition	Post Condition
Bridge No. 33-0047	Good	Good

Figure 35: Screen capture of the 2019 bridge NEEDs sheet, and 2020 SHOPP projects and report (bottom) used for comparison.

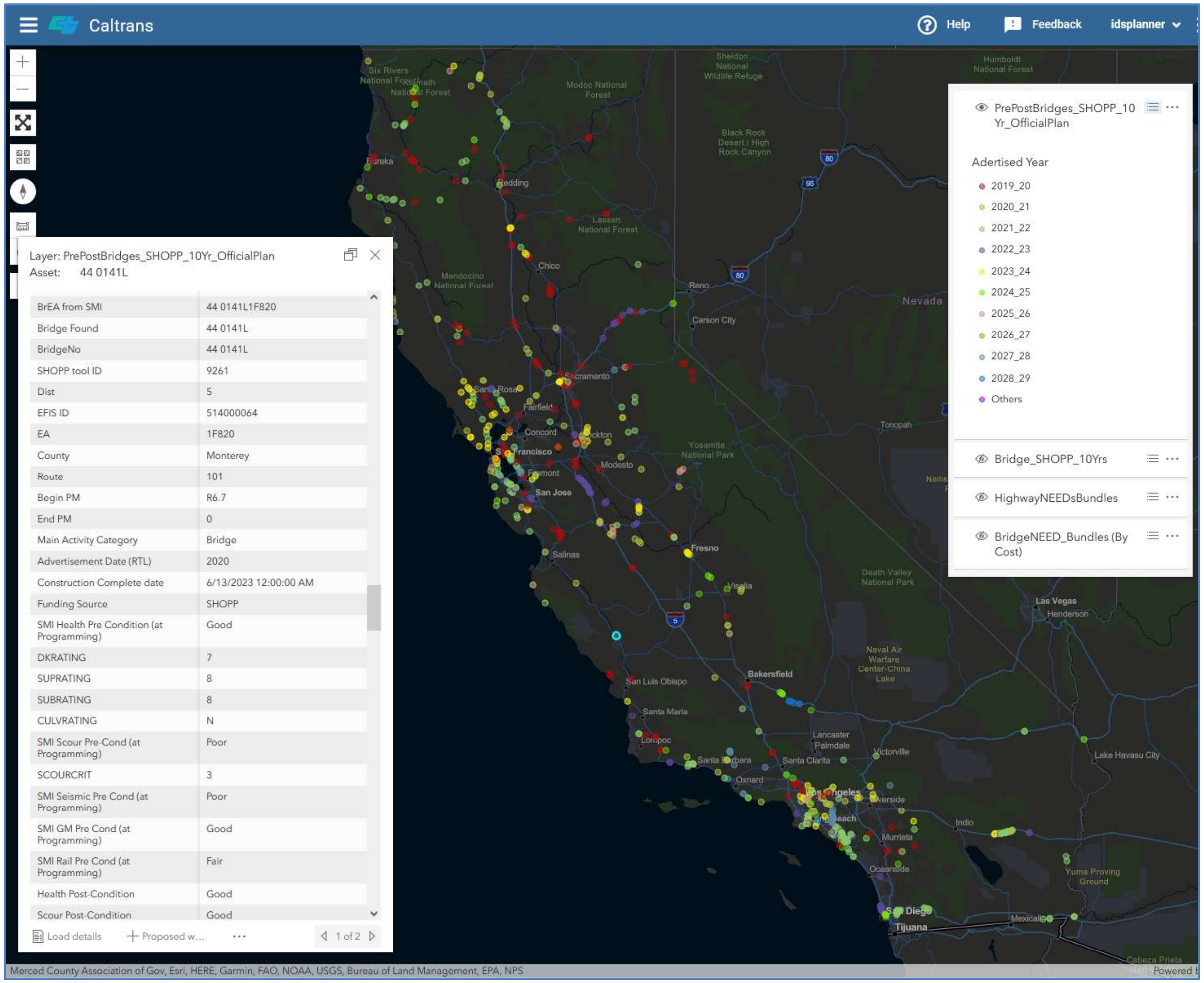


Figure 36: Map of bridge NEEDs and official SHOPP projects used for comparison

The pavement coarse segmentation data set included PaveM treatment recommendations, without specifying the year or the cost. The pavement SHOPP 10-year scenario assumed the same 4-year budget of the SHOPP program ($689 million, $586 million, $1,845 million, $1,387 million), and then assumed a constant budget of $1,387 million for the remaining years. SHS pavement treatments generated by the optimization algorithm were generally in good agreement with the treatment types produced by PaveM, in spite of the apparent differences in the models and analysis methodology. The treatment types considered in the optimization scenarios were aligned with the types employed by Caltrans for both flexible and rigid pavement. The flexible pavement treatments included thin, medium, and thick overlays, seal coat, cold-in-place recycling, and full depth reclamation. The JPC pavement treatments included grinding, slab replacement, grinding and slab replacement, concrete overlay, and lane replacement. A similar comparison of pavement SHOPP projects and scenario recommendations was also performed for District 4 (Figure 37).

Considering the differences between modeling assumptions in the proposed methodology and the current techniques employed by Caltrans for selecting SHOPP projects, the comparison between scenario results and actual SHOPP projects demonstrated a reasonable level of agreement of project selections. Refining and aligning the modeling assumptions to better reflect Caltrans practices and decision criteria will lead to a higher degree of agreement, leading to more consistent results and optimized project recommendations.

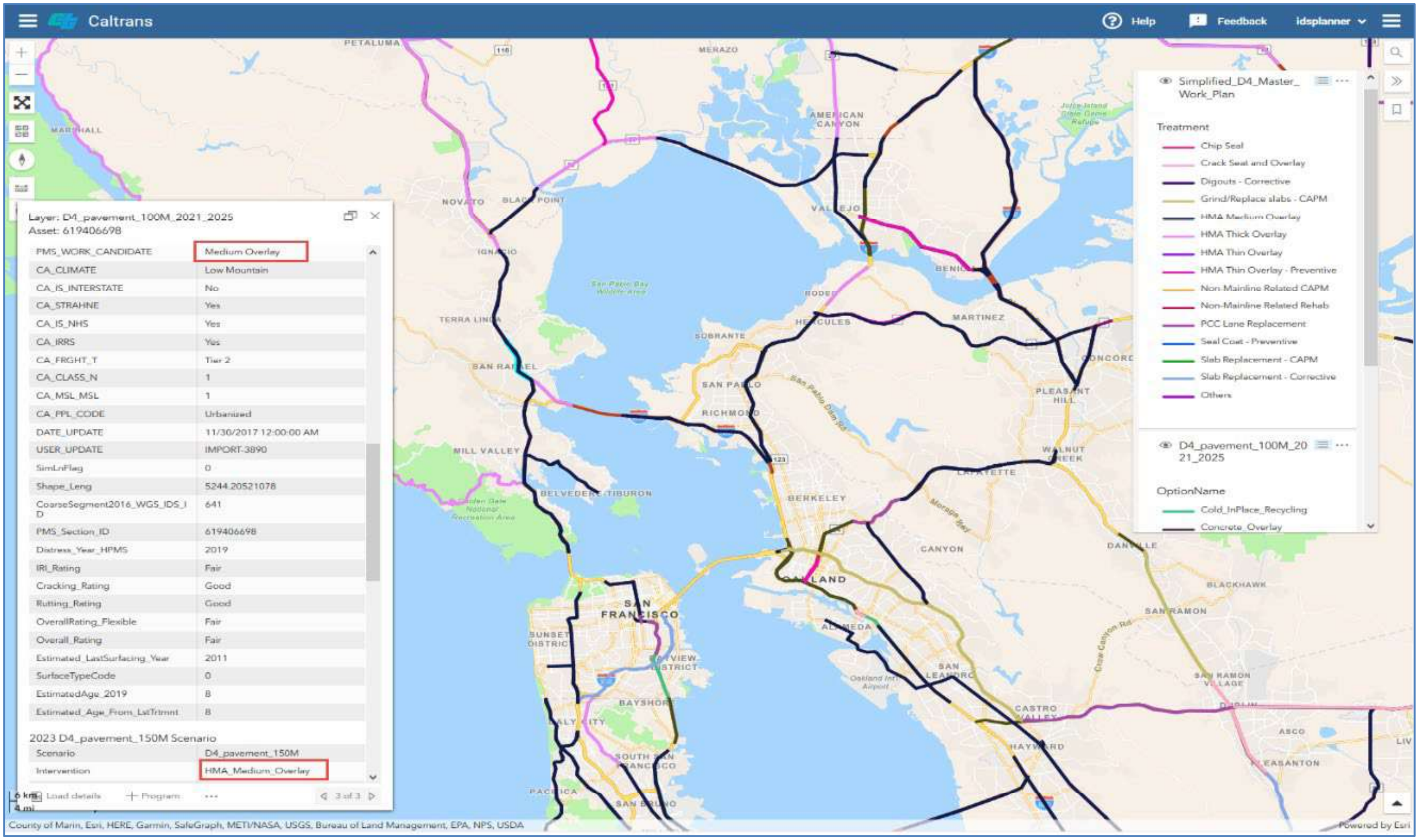


Figure 37: Map of District 4 pavement projects used for comparison

11 Example District-Level Cross-Asset Budget Allocation

In addition to the statewide analysis, modeling and planning scenarios were also developed for District 4 bridge and pavement inventory. This was intended to demonstrate a use case for performing district-level lifecycle modeling, planning, and project nomination. Analysis of District 4 bridges and pavements was performed using the same risk-based approach and lifecycle models proposed for statewide analysis. The same treatment models were used as well.

Multiple planning scenarios for District 4 bridges and pavements have been developed. Ten-year scenarios were developed for the district bridge inventory assuming annual investment levels of $100, $150, $200, and $300 million. Pavement scenarios were also developed assuming annual investment levels of $75, $100, $125, $150 million. These scenarios were analyzed following the same steps used to analyze statewide inventories. Similar to statewide analysis, while discrepancies were found for bridge treatments, there was a good agreement between pavement treatments recommended by our methodology and those proposed in the current Caltrans program.

For cross-asset budget allocation trade-off analysis, the relative weighting of bridge and pavement asset classes was calculated. Table 6 shows the calculation of the replacement values using age-based and condition-based approaches.

The average annual lifecycle cost for pavement and bridge assets, which is estimated using scenarios to calculate the annual required investment to maintain average status quo condition, was found to be $220 million and $1,256 million for District 4 pavement and bridge inventories, respectively. The current depreciated replacement value of bridges and pavement were found to be $16.38 billion and $4.9 billion, respectively.

Age-based replacement value was used for estimating relative asset class weights, which was found to be 0.8 and 0.2 for bridge and pavement asset classes, respectively.

Figure 38 shows an example of cross-asset budget allocation trade-off analysis for bridge and pavement assets in District 4.

Table 6. Replacement Value Calculation for District 4 Bridge and Pavement Inventory

Asset Class	Avg Life	Avg Condition*	Avg Age	Remaining Life% (Age-based)	Remaining Life % (Condition-based)*	Total Quantity	Unit Cost	As New Value	Replace Value
Bridges	75	38% Good; 54% Fair; 8% Poor	37	51%	71%	52 Million sq. ft	$635 /Sq. ft	$33 Billion	$16.83 Billion ($23.6 Billion)*
Pavement (AC)	20	23.7% Good; 74.6% Fair; 1.7% Poor	8	60%	72%	4,579 Lane Miles	$1.002 Million/ Lane Mile	$4.59 Billion	$2.75 Billion ($3.3 Billion)*
Pavement (JPCP)	40	18.1% Good; 71.4% Fair; 10.6% Poor	10	75%	67.5%	1,098 Lane Miles	$2.6 Million / Lane Mile	$2.86 billion	$2.15 Billion ($1.93 Billion)*

* Calculation based on asset current condition, assuming percentage of remaining life for good, fair, and poor assets to be 85%, 70%, and 20% for good, fair, and poor condition, respectively.

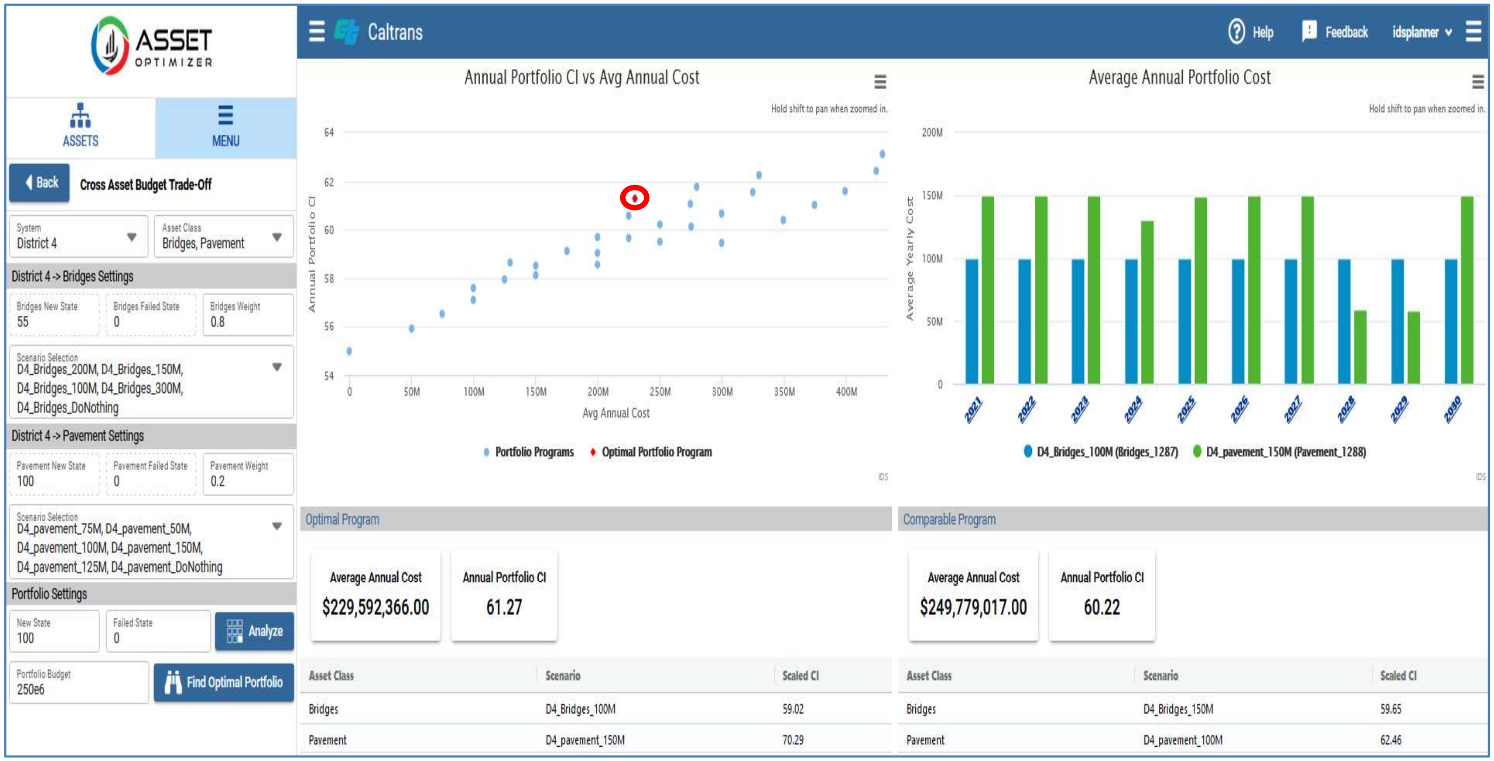


Figure 38: Cross-Asset Budget Allocation Trade-Off Analysis for Bridges and Pavements in District 4.

12 Methodology Applicability to Other Asset Classes

In the course of this study, the proposed cross-asset optimization methodology has been applied to SHS bridges and pavements. However, the same methodology can also be applied to other asset types such as culverts, traffic management systems, and other ancillary assets. In fact, over several years, the proposed methodology has already been successfully applied to a range of asset types including municipal, transit, utility, and marine assets. The genericity of the proposed methodology may be explained in the following points:

1. The configuration of performance variables, deterioration and risk models can be adapted to support different types of assets with varying levels of data availability. These models can be defined using different statistical distributions for one or multiple groups of assets. The models can also be developed based on the level of data availability. For example, when historical data is available, as in the case of SHS bridges, more detailed deterioration models that consider historical deterioration rates and patterns for different groups of assets can be defined. Also, when asset distress data is available, performance models can be defined to forecast the progression of these distresses and the condition of the assets. However, when detailed inspection or historical data are not available (e.g., in the example of culvert or TMS assets), simple age-based models based on estimated service life can be used. The flexibility of the modeling approach to accommodate different levels of data availability allows wider application of the approach to other asset types.
2. Definition of the treatment models are standardized for all asset types. The proposed methodology allows the definition of any number of treatments (or treatment combinations) and associated cost and benefits models. Benefits are defined as incremental improvements to various performance variables. Each treatment can be associated with a set of rules (or constraints) that determines its feasibility. Most of the treatment criteria can be easily captured using these rules. Treatment models are defined using consistent models and format, irrespective of the asset class.
3. The multi-objective optimization algorithm is asset-agnostic, and can be applied to any set of assets, associated with any set of treatments. The optimization algorithm was formulated and implemented to require minimal configuration and to automatically adapt to the size of the problem to ensure convergence to an optimal solution within a reasonable timeframe.
4. The proposed techniques for CapEx/Opex trade-off, cross-asset budget distribution, and project bundling analyses are applicable to any asset type.
5. The programming and budgeting processes apply to projects, irrespective of the impacted types of assets. The same processes for managing program workflows, MODA, project nomination, funding allocation, and tracking of projects, are all applicable to any asset classes.

13 Conclusion

TAM programming decision-making is inherently an integrated cross-asset and multi-objective process that requires the assimilation of a multitude of data and models, involving system-level trade-offs to optimize project selections and budget allocations, while considering performance targets and risk levels across all asset classes. This project proposed a novel cross-asset optimization methodology to support Caltrans TAM programming and budgeting decisions and processes across the entire transportation asset portfolio. The proposed methodology integrates Caltrans' project-level MODA model, with cross-asset system-level optimization model that enables optimal development and management of programs and budgets. The application of the methodology has been demonstrated using the Asset Optimizer software tools, which was successfully applied on Caltrans' SHS bridges and pavements.

Based on robust optimization and analysis procedures, the proposed methodology integrated asset-level, system-level, and program-level analyses in a single framework. Combining these multiple types of trade-off analyses was extremely useful in supporting efficient information flow between inter-dependent decision-making processes, and informing decisions on performance target setting, project selection and prioritization, multi-year program development, and budget allocation. Novel techniques have been proposed for selecting optimal treatment types and timing, performance and risk modeling of asset classes, analyzing what-if scenarios, performing capital versus maintenance investment trade-off analysis, optimizing budget distribution among different asset classes, and performing bundling analysis.

The proposed methodology, and associated software tool, would represent a key component in the wider context of supporting agency or statewide asset management processes. Efficient implementation of this methodology would require close integration with other external systems and data sources (e.g., asset registries, project management systems, etc.). Lack of industry-wide data standards, with the exception of NBI and HPMS data, presents a significant challenge for efficient data integration and systems interoperability. Ideally, a system implementing this methodology would serve as "an integrator" that can ingest and process data coming from disparate systems, effectively use the data to enable trade-off analyses and cross-asset optimization, and support managing programs and budgets.

Implementation of the methodology across Caltrans' districts could promote the application of a common framework for analysis and decision-making, thus supporting more consistent processes for performance target setting, projects selection, and funding allocation, and ultimately leading to more consistent management processes, closer coordination and increased transparency. The methodology may also be applied at the level of MPOs and local agencies to support a wider statewide coordination and consistency.

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Appendix A:

Preliminary Life Cycle Modeling and Planning Scenarios of Caltrans SHS Bridges

A.1 Data Sources and Analysis

In this analysis, we considered the entire Caltrans NBI data (1992-2020). The SHS bridges are identified as follows: NBI Item 22 is “1”, span length >=20 feet, and have “route is carried on the structure (Item 5A or Record Type is “1”). All 946 culverts were excluded from the analysis. Initial modeling and analysis were performed on 2018 data set, and later updated based on 2019, and then 2020 data set. Details of the analysis can be accessed in the Asset Optimizer software.

Based on 2018 NBI data, Caltrans SHS bridge inventory includes 11,458 SHS bridges, with a total deck area of approximately 244 million square feet (22.7 million square meters). Bridge material (NBI Item 43A) is largely dominated by concrete (54% by count, 40% by deck area), prestressed concrete (39% by count, 46% by deck area), and steel (5% by count and 13% by deck area). The type of design/construction (Item 43B) is dominated by box girders (60% by count, 69% by deck area), slab (16% by count, 5% by deck area), T-beam (11% by count, 7% by deck area), and stringer/multi-beam types (9% by count, 12% by deck area) (Figure 39). Figure 40 shows the breakdown of SHS bridges by both material and design type.

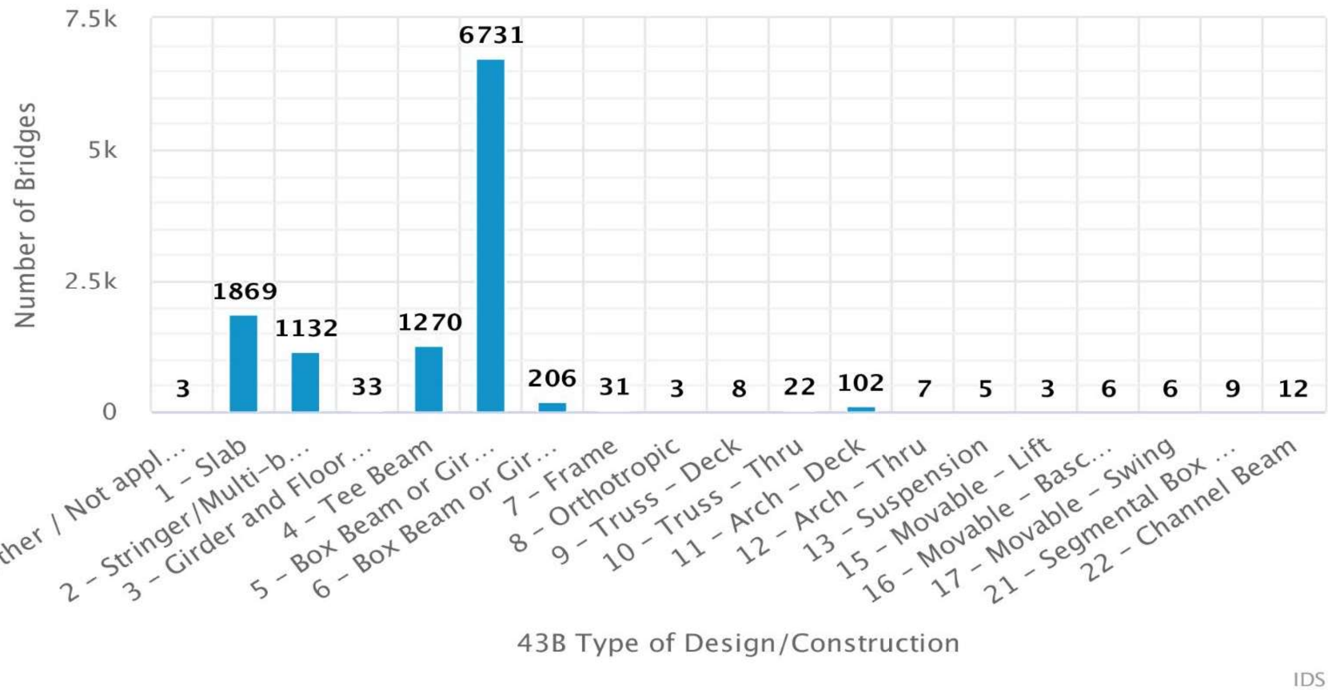


Figure 39: Number of SHS bridges by Design/Construction Type (Item 43B)

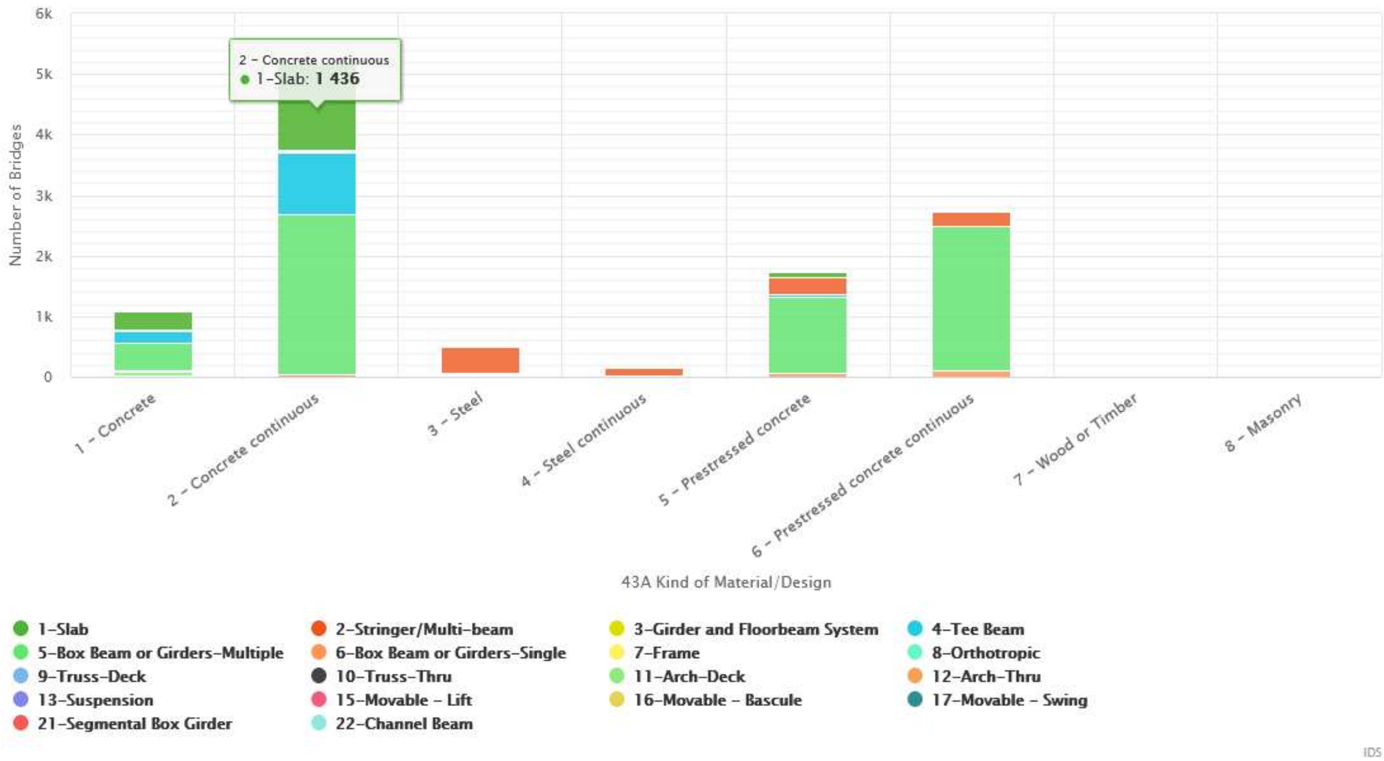
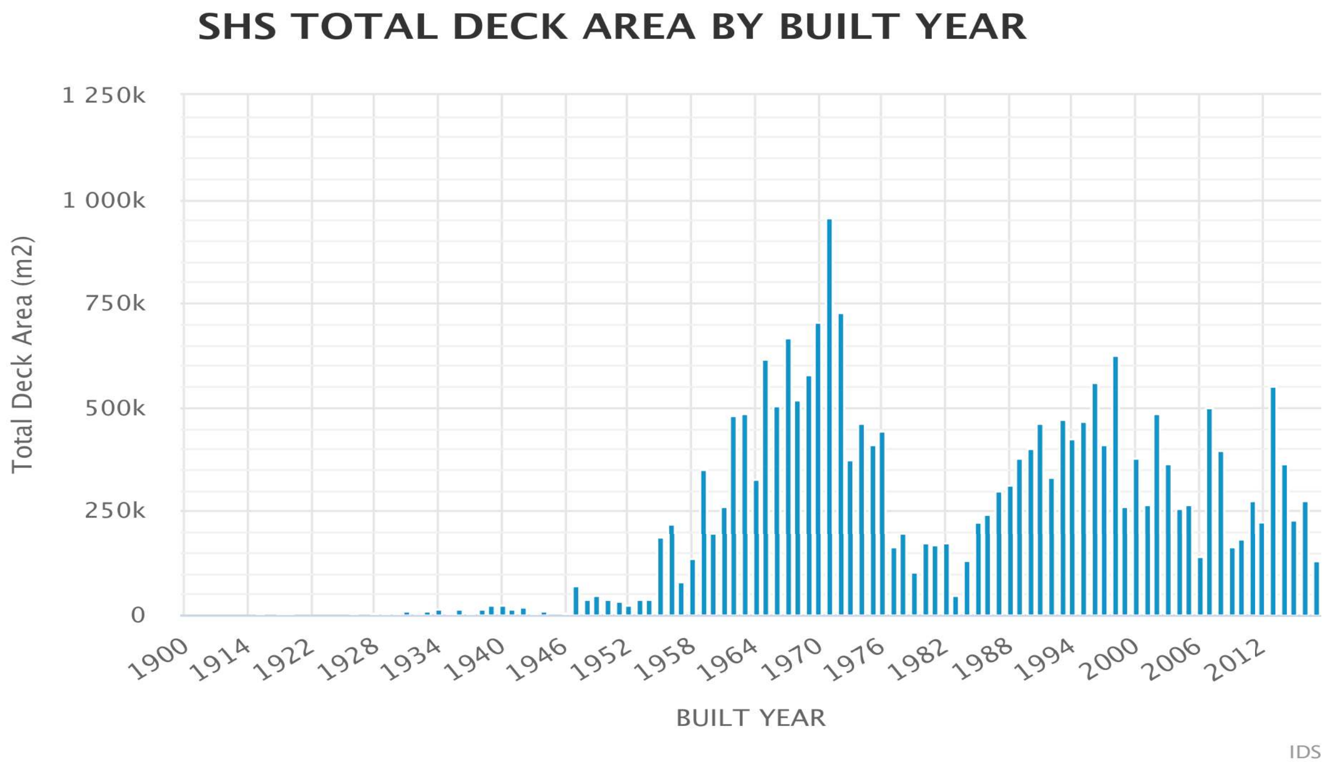


Figure 40: Number of SHS bridges by Material and Design type (Items 43A and 43B)

Caltrans has a relatively aging bridge population, with an average age of 37.5 years, whereas the median age is 43 years. Age is calculated as the difference between the inspection year (NBI Item 90) and Year Built (Item 27) or Year Reconstructed (Item 106). Figure 41 shows the distribution of SHS construction year (by total deck area) and age. Many of Caltrans SHS bridges that were built during the 1960s and 1970s are reaching end of their service life, and therefore, are expected to experience a faster rate of deterioration over the coming few years.

The age boxplot shows that the 1st quartile (25% percentile) of the age values is 22 (i.e., 25% of SHS bridges have age less than 22 years), and the 3rd quartile (i.e., 75% percentile) is 51 years (i.e., 75% of bridges have age less than 51 years). The interquartile range (IQR) (or the middle fifty percent of the age values) indicates that the 50% all SHS bridges have age between 22 and 51 years. IQR indicates the statistical dispersion of the data, and is considered as a better metric of data dispersion than the range value (or maximum minus minimum). The 2nd and 98th percentile of the age values are 2 and 77 years, respectively (i.e., 98% of the bridges have an age of less than 77 years, while only 2% of the bridges have an age less than 2 years).



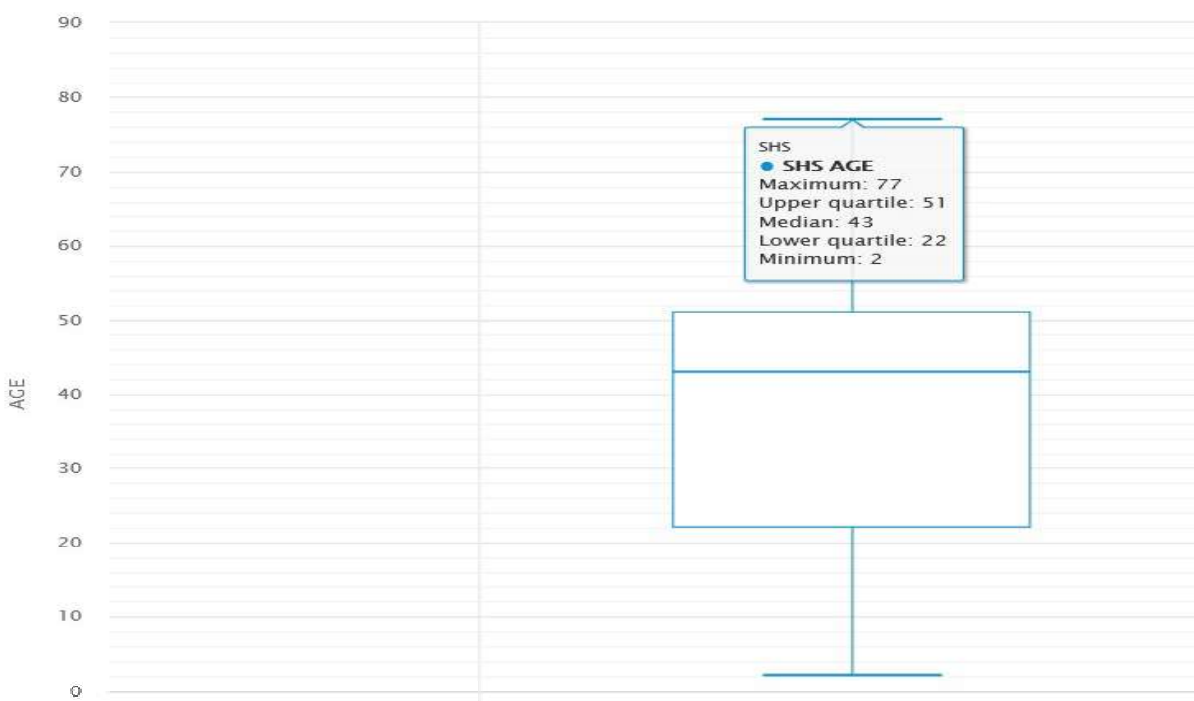


Figure 41: Number of SHS bridges by Built Year

NBI 2018 data shows the SHS inventory with approximately 64% of total deck area in good condition, 31% in fair condition, and 4.85% in poor condition (Figure 42).

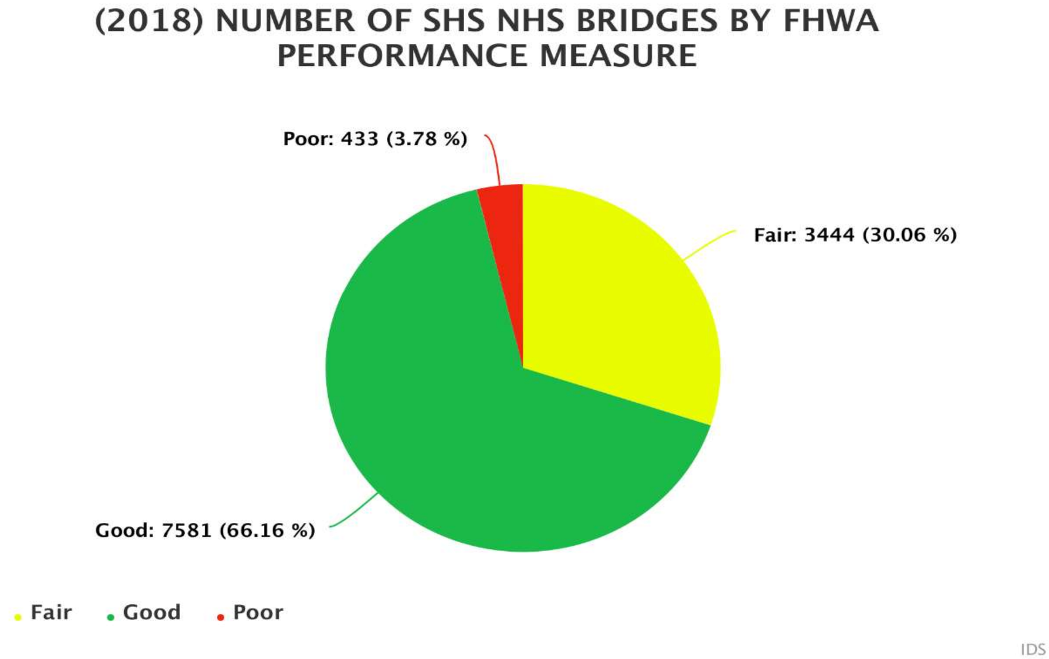
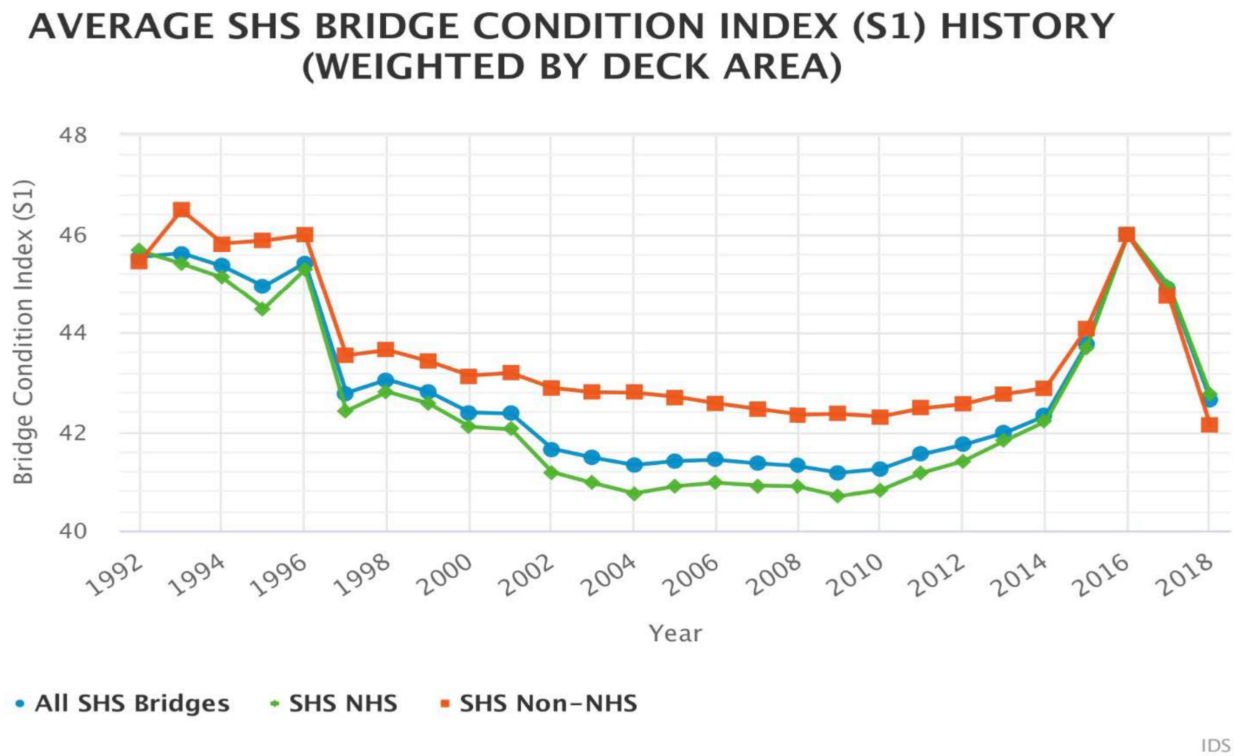


Figure 42: FHWA Performance Measure for SHS Bridges based on NBI 2018 Data by deck area

Examining historical trends of system performance can provide valuable insights into the rate of system deterioration (and improvements), which would have significant implications on the development of asset management plans and assessing future financial requirements to maintain the system in a state of good repair.

Caltrans NBI data for SHS bridges showed a historical trend of continuous degradation of average condition until approximately 2008, followed by a steady increase in system-average condition until 2016. A return to the deterioration trend was observed in 2017 and 2018. Figure 43 shows the trend of the bridge condition index (CI or S1) and risk index (RI) for the SHS bridge inventory.

The data also showed that the accelerated deterioration between 1992 and 2008 was primarily attributed to the deterioration of deck condition, as shown in Figure 44. Figure 45 shows the total distribution of good, fair, poor bridges by count and deck area for 2008 (worst year) and 2016 (best year). Figure 46 shows the historical distribution, by count and by total deck area, of SHS bridges based on the FHWA performance measure. Table 7 shows the historical trend of good, fair, poor bridges for SHS, SHS-NHS, and SHS-Non-SHS by percentage of count and deck area.



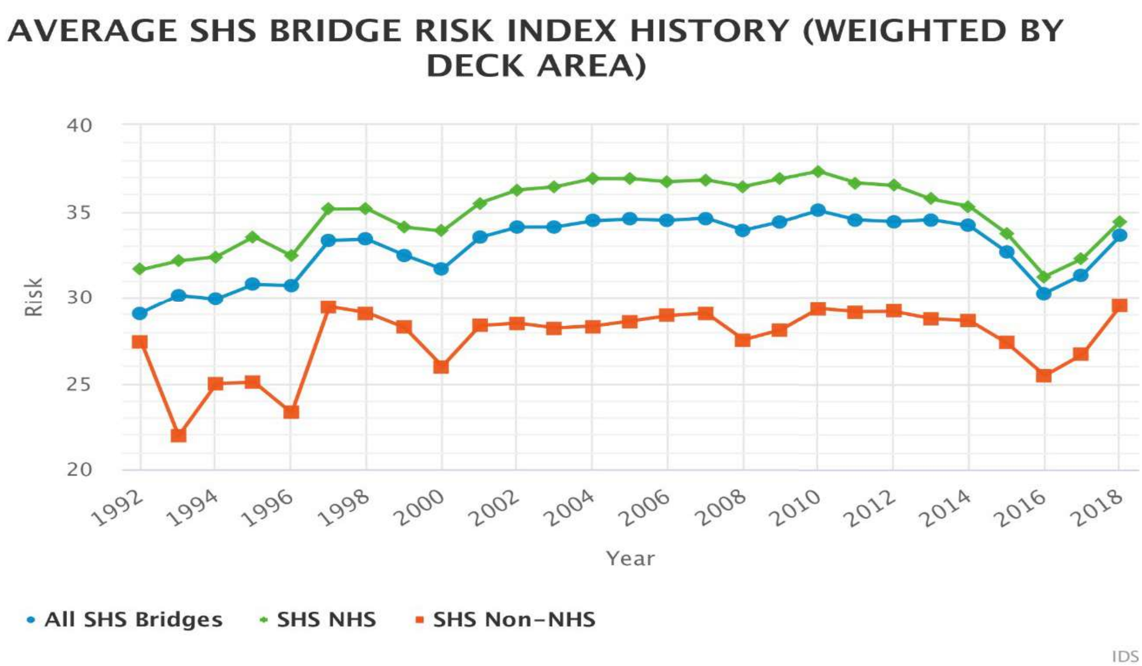


Figure 43: Historical trend of average Condition Index (top) and Risk Index (bottom) for SHS bridges (weighted by total deck area)

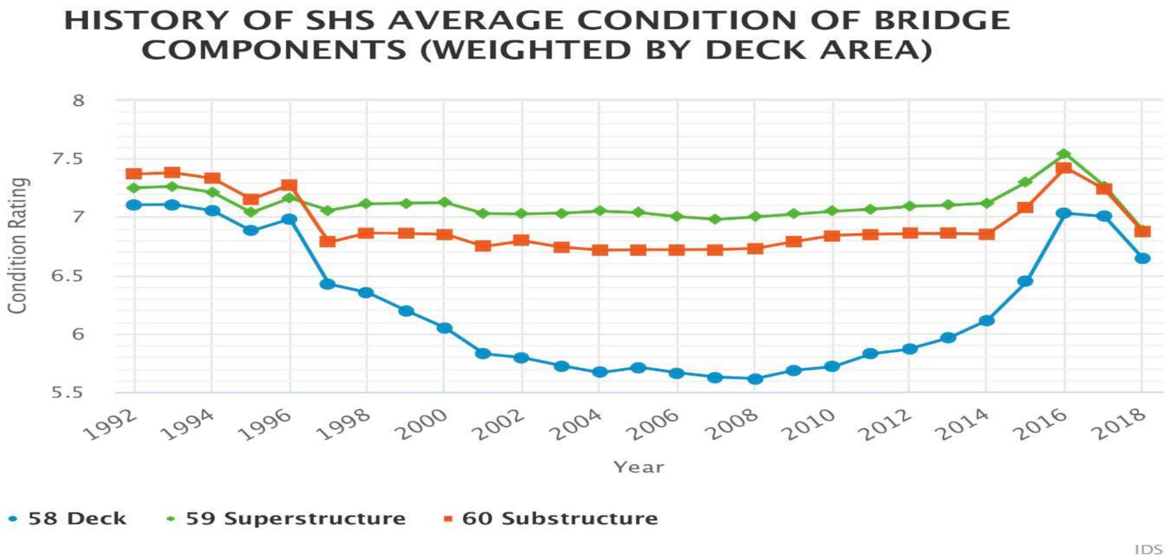


Figure 44: Historical trend of weighted-average condition of deck, superstructure, and substructure

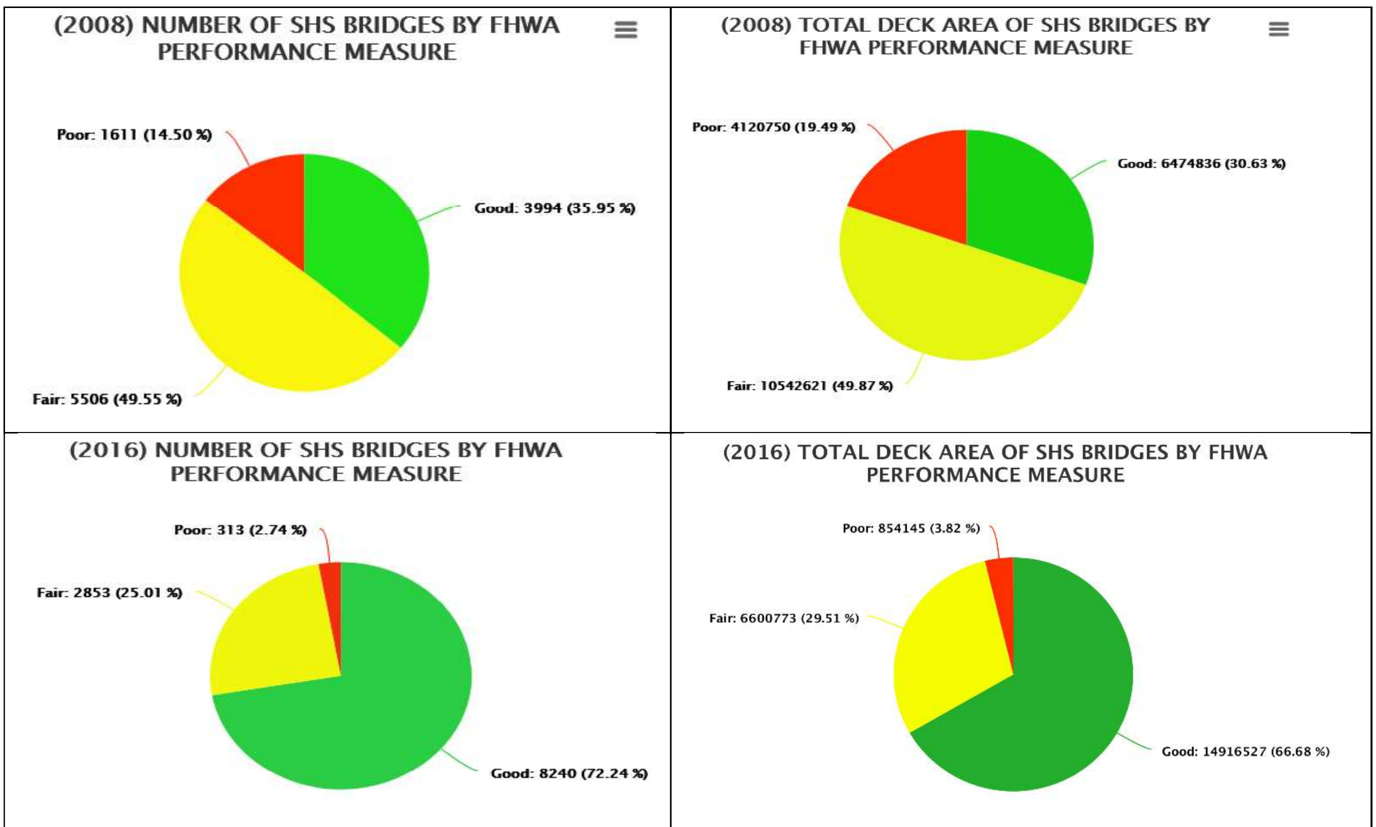
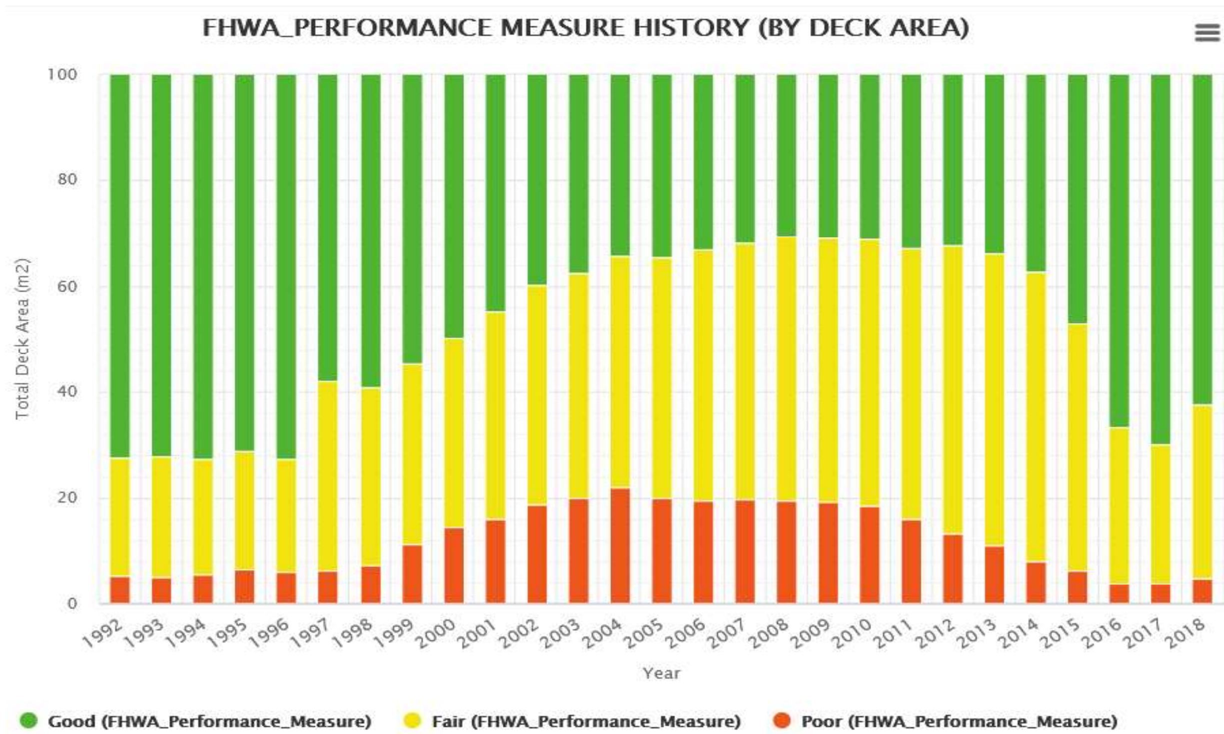


Figure 45: FHWA Performance Measure for SHS Bridges by count and deck area



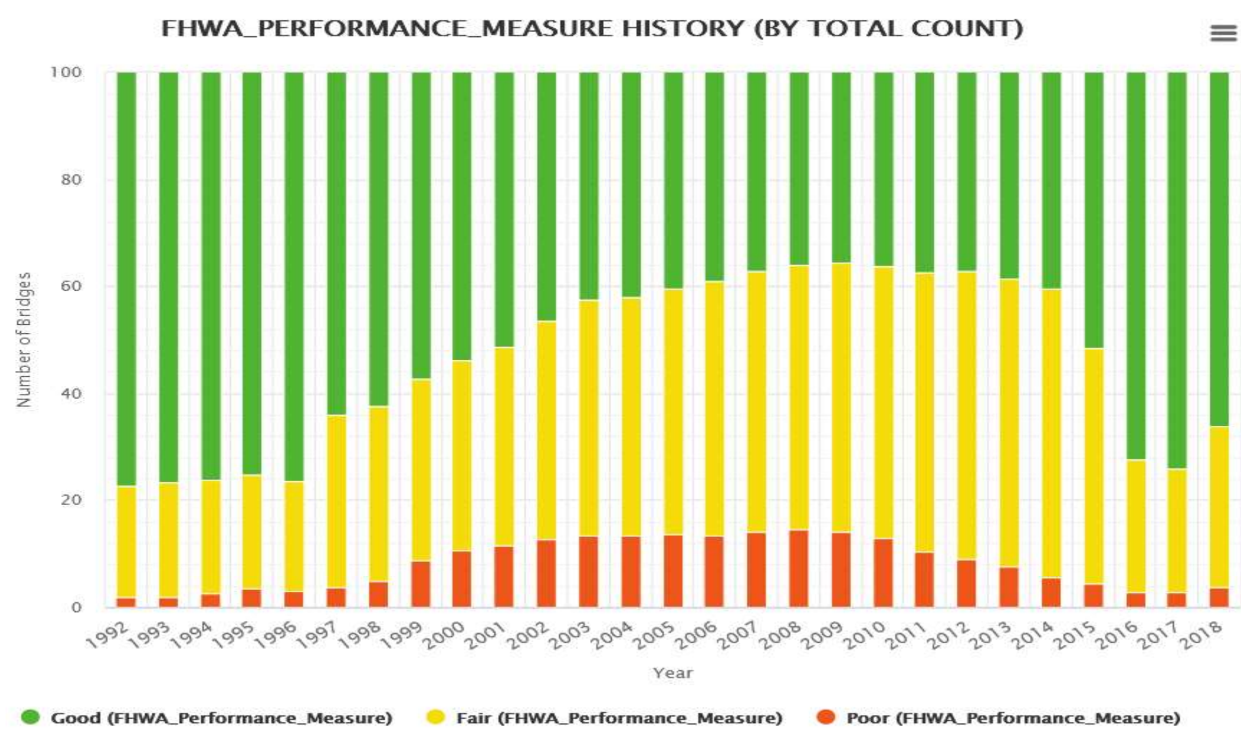


Figure 46: FHWA Performance measure for SHS bridges (by deck area- top, by count-bottom)

Table 7. Historical Percentage of Good, Fair, Poor Bridges for SHS, SHS-NHS, and SHS-Non-NHS

All SHS Bridges						
Year	Poor		Fair		Good	
	% Count	% Area	% Count	% Area	% Count	% Area
1992	1.91%	5.31%	20.63%	22.38%	77.46%	72.32%
1993	1.91%	5.02%	21.49%	22.70%	76.60%	72.29%
1994	2.52%	5.57%	21.22%	21.72%	76.26%	72.70%
1995	3.43%	6.55%	21.37%	22.17%	75.20%	71.28%
1996	2.91%	5.87%	20.71%	21.27%	76.38%	72.87%
1997	3.79%	6.20%	32.28%	35.58%	63.93%	58.22%
1998	4.89%	7.31%	32.76%	33.43%	62.35%	59.27%
1999	8.74%	11.19%	33.95%	33.91%	57.31%	54.91%
2000	10.65%	14.50%	35.52%	35.73%	53.83%	49.78%
2001	11.60%	15.91%	37.19%	39.24%	51.21%	44.85%
2002	12.60%	18.74%	40.93%	41.48%	46.47%	39.79%
2003	13.32%	20.00%	44.11%	42.50%	42.57%	37.49%
2004	13.42%	21.93%	44.68%	43.79%	41.90%	34.28%
2005	13.63%	19.79%	46.05%	45.70%	40.31%	34.50%
2006	13.48%	19.46%	47.55%	47.48%	38.97%	33.07%
2007	14.08%	19.74%	48.65%	48.39%	37.27%	31.87%
2008	14.50%	19.48%	49.55%	49.85%	35.95%	30.67%
2009	14.19%	19.16%	50.13%	49.94%	35.67%	30.90%
2010	12.96%	18.37%	50.87%	50.60%	36.17%	31.03%
2011	10.44%	16.03%	52.09%	51.10%	37.47%	32.87%
2012	9.06%	13.18%	53.65%	54.54%	37.29%	32.28%
2013	7.51%	11.07%	54.01%	55.01%	38.48%	33.92%
2014	5.58%	8.00%	53.92%	54.75%	40.50%	37.24%
2015	4.33%	6.28%	44.12%	46.69%	51.55%	47.03%
2016	2.74%	3.82%	25.01%	29.50%	72.24%	66.68%
2017	2.84%	3.78%	23.08%	26.26%	74.08%	69.97%
2018	3.78%	4.62%	30.06%	32.92%	66.16%	62.45%
SHS-NHS						
1992	0.80%	5.05%	16.69%	22.80%	82.51%	72.16%
1993	1.37%	5.58%	19.39%	23.60%	79.24%	70.81%
1994	2.15%	6.18%	19.96%	24.08%	77.89%	69.74%
1995	3.50%	7.93%	20.35%	24.47%	76.15%	67.59%
1996	2.66%	6.25%	18.61%	21.88%	78.73%	71.87%

1997	4.02%	7.82%	31.80%	36.93%	64.18%	55.26%
1998	5.41%	8.73%	33.56%	34.14%	61.03%	57.14%
1999	9.76%	12.32%	34.63%	34.32%	55.61%	53.35%
2000	11.60%	15.94%	36.22%	36.33%	52.18%	47.73%
2001	12.65%	17.76%	37.62%	40.55%	49.73%	41.69%
2002	13.89%	21.56%	40.85%	41.53%	45.27%	36.92%
2003	14.98%	23.48%	43.91%	41.52%	41.11%	35.01%
2004	15.13%	26.41%	44.32%	42.71%	40.55%	30.88%
2005	15.07%	23.14%	45.52%	44.78%	39.41%	32.08%
2006	15.21%	22.54%	46.53%	46.57%	38.26%	30.89%
2007	15.91%	22.54%	47.39%	47.22%	36.70%	30.24%
2008	16.40%	22.06%	47.83%	48.59%	35.78%	29.36%
2009	15.80%	21.87%	48.69%	48.38%	35.51%	29.75%
2010	14.08%	20.79%	49.38%	49.36%	36.54%	29.85%
2011	11.02%	18.15%	51.35%	49.93%	37.63%	31.92%
2012	9.64%	14.81%	52.40%	53.14%	37.96%	32.05%
2013	7.86%	12.10%	52.81%	53.85%	39.34%	34.05%
2014	5.60%	8.53%	52.97%	53.85%	41.43%	37.62%
2015	4.33%	6.66%	43.16%	46.26%	52.51%	47.08%
2016	2.83%	4.17%	23.60%	29.08%	73.57%	66.75%
2017	2.86%	4.02%	21.01%	25.17%	76.13%	70.81%
2018	3.74%	4.85%	27.88%	31.37%	68.38%	63.78%
SHS Non-NHS						
1992	2.43%	5.47%	22.47%	22.11%	75.09%	72.42%
1993	3.19%	2.72%	26.50%	18.98%	70.31%	78.30%
1994	3.06%	4.36%	23.02%	16.98%	73.92%	78.67%
1995	3.34%	3.66%	22.87%	17.36%	73.79%	78.98%
1996	3.55%	4.24%	25.93%	18.61%	70.52%	77.15%
1997	3.43%	2.70%	33.01%	32.68%	63.56%	64.63%
1998	4.07%	3.87%	31.50%	31.70%	64.44%	64.43%
1999	7.10%	8.23%	32.85%	32.82%	60.05%	58.95%
2000	9.14%	10.77%	34.41%	34.17%	56.45%	55.06%
2001	9.91%	11.15%	36.52%	35.87%	53.57%	52.98%
2002	10.56%	11.41%	41.06%	41.36%	48.38%	47.23%
2003	10.71%	11.21%	44.42%	45.00%	44.87%	43.80%
2004	10.74%	10.67%	45.24%	46.48%	44.02%	42.84%
2005	11.36%	11.28%	46.90%	48.05%	41.74%	40.67%
2006	10.74%	11.69%	49.17%	49.76%	40.09%	38.55%

2007	11.18%	12.63%	50.67%	51.38%	38.16%	35.99%
2008	11.50%	12.98%	52.29%	53.03%	36.21%	34.00%
2009	11.66%	12.28%	52.41%	53.88%	35.94%	33.83%
2010	11.20%	12.35%	53.22%	53.70%	35.58%	33.95%
2011	9.52%	10.76%	53.27%	54.01%	37.21%	35.24%
2012	8.13%	9.13%	55.63%	58.03%	36.24%	32.84%
2013	6.53%	6.06%	57.44%	60.65%	36.03%	33.29%
2014	5.54%	5.42%	56.63%	59.19%	37.82%	35.39%
2015	4.33%	4.41%	46.85%	48.80%	48.82%	46.79%
2016	2.49%	2.08%	29.04%	31.59%	68.46%	66.33%
2017	2.79%	2.57%	28.97%	31.59%	68.25%	65.84%
2018	3.90%	3.53%	36.27%	40.55%	59.83%	55.93%

A.2 Data Limitations for Deterioration Modeling

Deterioration models should represent the natural rate of condition degradation due to aging, and without considering any condition improvements due to maintenance actions. Bridges that experience faster rate of deterioration typically undergo more frequent and/and extensive maintenance and preservation activities (e.g., deck overlay/repair, deck replacement, etc.) to rectify defects and ensure safety. Absence of maintenance history often pose a challenge for modeling bridge deterioration. Information on the type, frequency, and criteria of maintenance actions would be required to assess the natural deterioration of bridge components and the impact of maintenance actions on the condition. In absence of this information, the data should be filtered to remove records indicating occurrence of maintenance actions. Figure 47 shows historical trend of deck condition for some concrete box girder bridges.

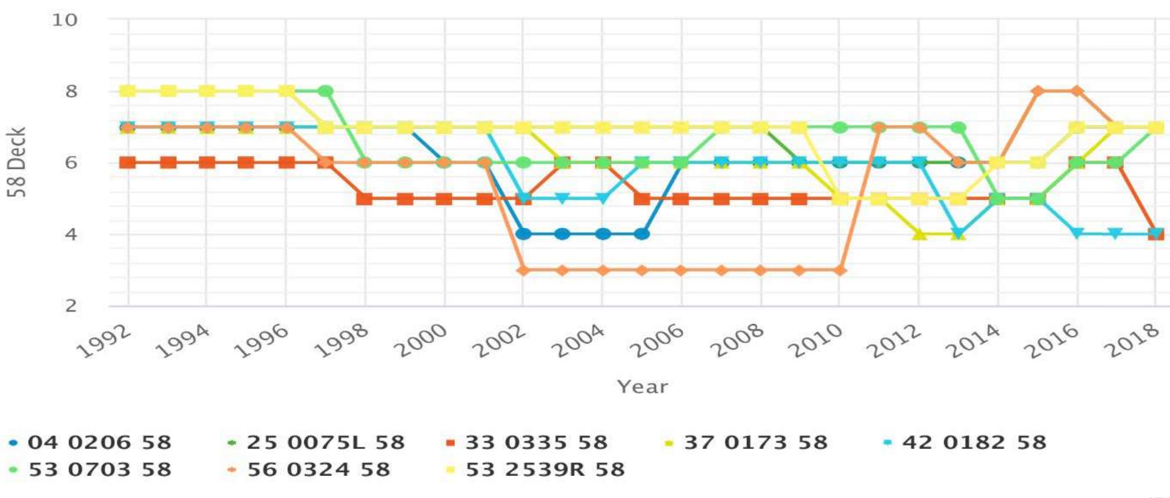


Figure 47: Changing deck condition due to deterioration and maintenance actions

Another challenge, also caused by the absence of maintenance history data, is that the distribution of bridge inspection data may show misleading trends or inaccurate correlations. For example, in some cases we may find a negative correlation between a bridge age and the condition of its components, where components in older bridges, which may have undergone rehab actions or replacements, would have better condition than similar newer bridges. Figure 48 illustrates this issue where the distribution of SHS deck condition and age shows a median age of bridges in fair deck condition (5) to be 30 years, whereas bridges in very good condition deck (8) have a median age of 42. Decks with bridge age > 40 and condition states of 7 or 8, were most likely replaced or subjected to extensive maintenance and rehab work. Also, when a deck is replaced, this information is not reflected in NBI data because Item (27 Built Year) only references the construction year of the entire bridge structure.

To overcome the lack of correlation between age and condition, some modelers use "age restrictions" to filter records that have condition inconsistent with their age. In this approach, the data is interval-censored to only allow records that have age within specific ranges for each condition state (e.g., assume that valid records with very good deck condition would have a maximum age of 15 years).

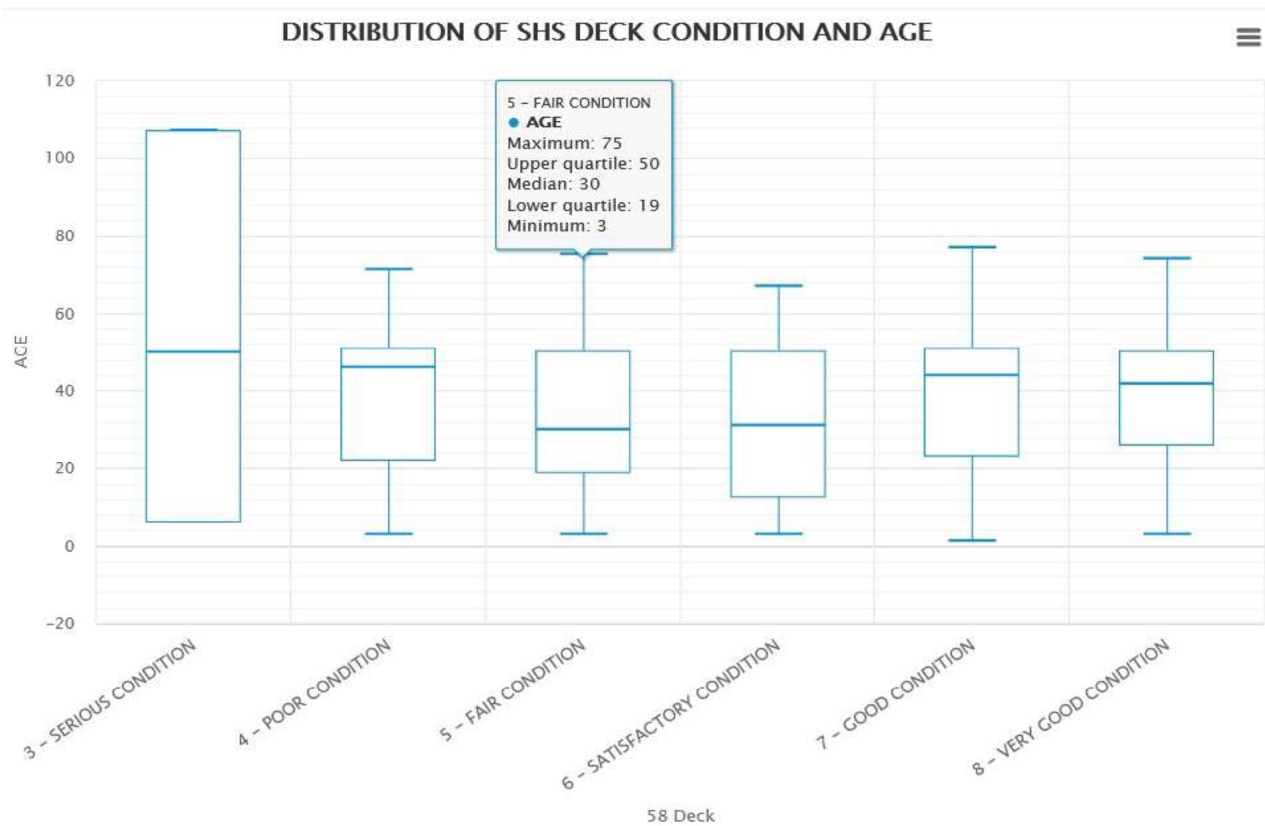


Figure 48: Boxplot of age of SHS bridges for each deck condition state, showing decks in condition 7 and 8 to have a higher median age than bridges in condition 4 and 5

This issue may also pose a challenge when trying to correlate other deterioration factors with bridge condition. For example, in some situations, bridges with higher truck traffic, which would deteriorate faster and need more frequent treatments, may be shown to have better condition than bridges with lower truck traffic.

Bridges are typically repaired (or closed) once starting to deteriorate to a serious condition state. As a result, sufficient data on bridges in poor condition may not be available. Another challenge often found in bridge data is that the distribution of condition data may not represent all possible condition states, which results in lacking enough samples of bridges in poor condition. For example, the frequency distribution of Caltrans SHS deck condition by age (Figure 49) shows the majority of bridge decks in condition states 5,6,7,8 with minimal data points for other condition states (1,2,3,4). Also, no bridges in 2018 data were shown to be in condition 9.

Because of the data limitations described above, many agencies still rely on expert elicitation to define bridge deterioration models, in spite of the presence of significant amount of historical bridge inspection data. To utilize available inspection data for deterioration modeling, and in absence of maintenance data, the inspection data should be censored (or truncated) to exclude records indicating condition improvements and only use records indicating deterioration due to aging. In this study, we used a data-driven approach based on historical inspection records after processing the data over the 27 years history of NBI data, as described in the next section.

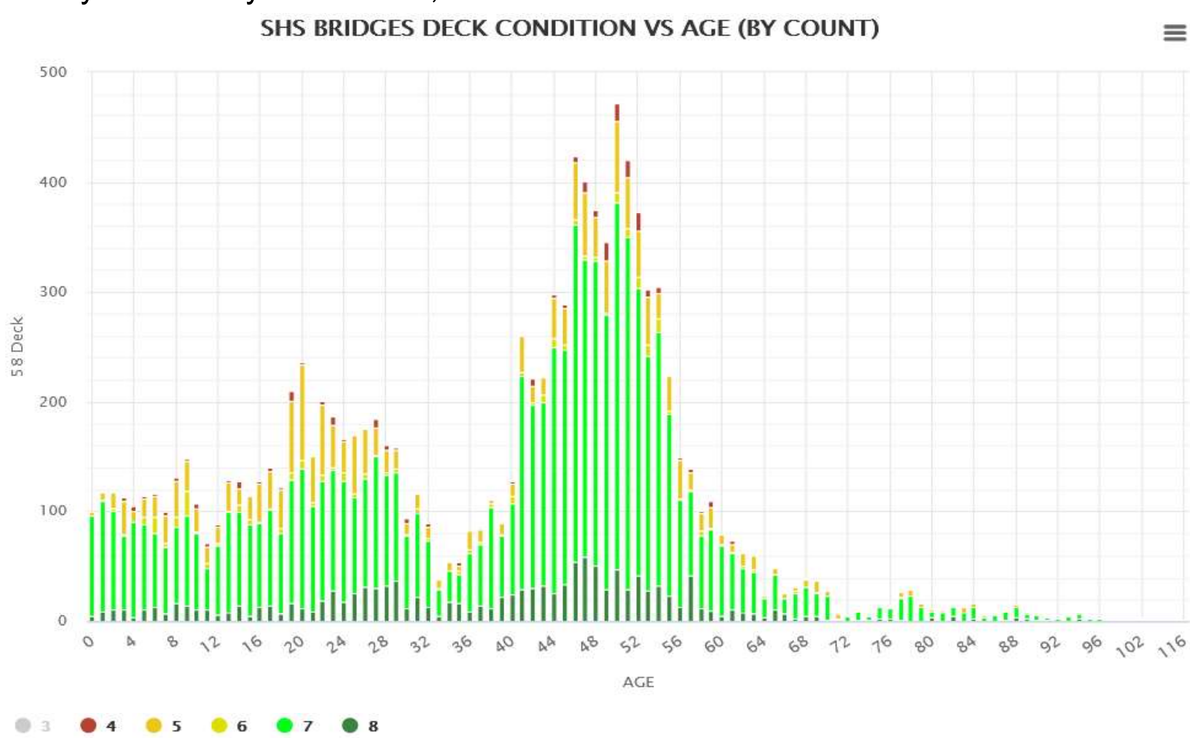


Figure 49: Frequency distribution of SHS deck condition and bridge age (2018 NBI data)

A.3 Performance and Risk Modeling Approach of Caltrans Bridge Inventory

We propose to use a risk model based on a modified version of the FHWA Sufficiency Rating (SR) formula and Iowa DOT Priority Ranking formula. The model defines modified equations of the four SR factors, S1, S2, S3, and S4, and adds a factor, S5 (Figure 50). Each of these factors measures a specific aspect of the bridge risk. Collectively, these factors would provide a comprehensive measure for evaluating the "relative" risk of failure of bridges, that can guide the project selection process.

In summary, S1 measures the structural condition and adequacy of a bridge based on the condition of its key components (deck, superstructure, substructure, and load capacity). The value of S2 measures the bridge's geometrics and functional obsolescence taking into consideration under-clearance adequacy (NBI Item 69), waterway adequacy (NBI Item 71), and roadway lane width (NBI Items 51 and 28). The value of S3 reflects the bridge's essentiality for the public, taking into account traffic volume (NBI Item 29), detour length if the bridge is closed (Item 19), and whether the roadway is on the National Highway System (Item 104). The value of S4 takes into account whether the bridge is fracture critical or fatigue vulnerable (Items 92A and 92C) and channel protection (Item 61). The value of S5 takes into account for scour and seismic criticality, which are of particular importance for Caltrans bridges. These five measures are calculated based on NBI items as explained below.

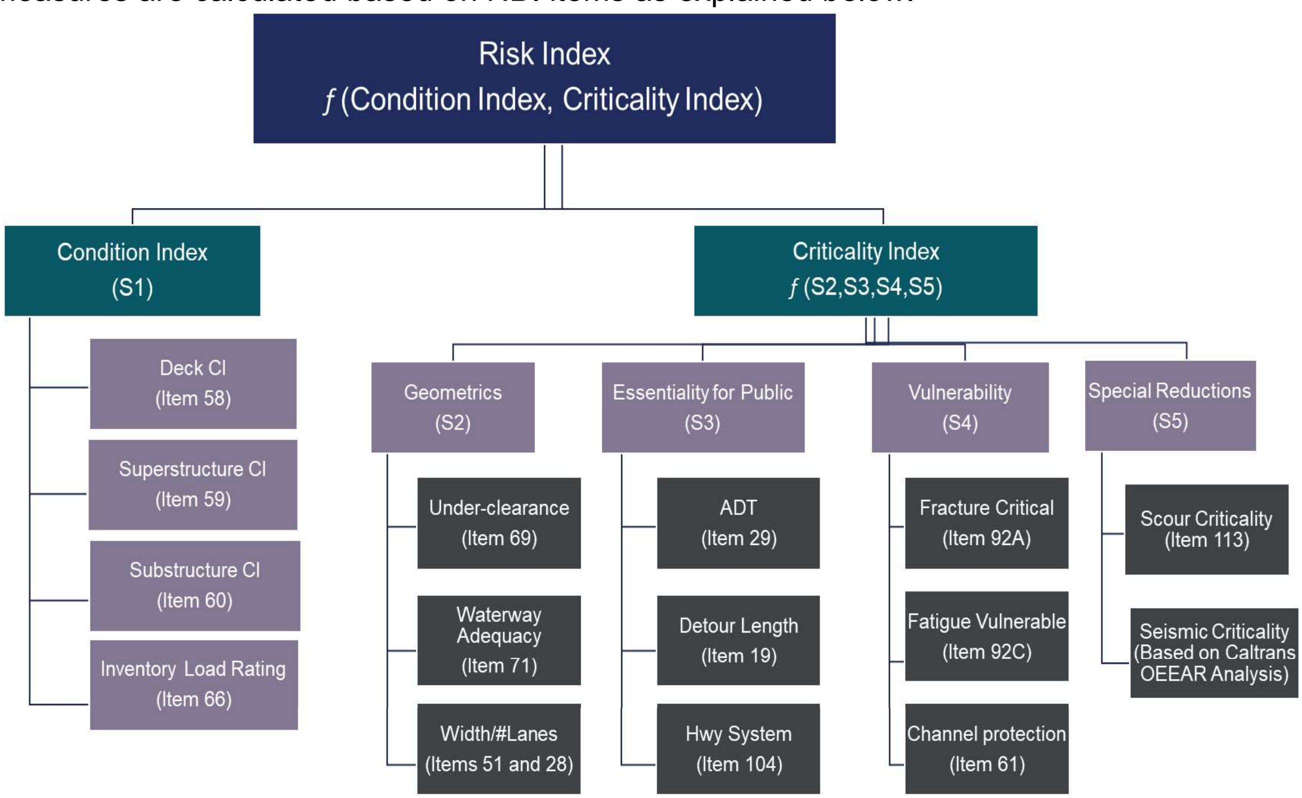


Figure 50: Proposed Bridge Risk Model

Structural Adequacy and Safety

Structural adequacy is measured using S1, which indicates the bridge's structural condition and is used as a surrogate for Condition Index (CI). S1 is calculated based on deck, superstructure, and substructure condition, as well as the inventory load rating, using the following equation:

S1 = 55 - (A+B+C+E)

Where, A, B, C, and E are reduction factors and estimated based on NBI condition ratings of superstructure (Item 59), substructure (Item 60), deck (Item 58), and inventory load rating (Item 66), respectively. The values of the reduction factors, A, B, and C are estimated as shown in Table 8.

Table 8. Values of Condition Reduction Factors

NBI Rating	A (Based on Item 59 Superstructure)	B (Based on Item 60 Substructure)	C (Based on Item 58 Deck)
N or 9	0	0	0
8	2	2	1
7	4	4	2
6	7	7	4
5	10	10	6
4	13	13	9
3	15	16	12
<= 2	20	20	15

The load carrying capacity reduction factor, E, is calculated based on the inventory load rating (NBI Item 66). The value of E is calculated as follows:

Case 1: If item 65 = 0, 1, 2, 3, 4, 5, A, B, C (i.e., inventory rating reported in metric tons)

$E = (32.4 - \text{Item } 66/10)^{1.5} \times 0.3254 \times 0.5 \geq 0$

Case 2: If item 65 = 6, 7, 8, D, E, F (i.e., inventory rating reported by rating factor)

$E = \{(1 - \text{Item } 66/100)*32.4\}^{1.5} \times 0.3254 \times 0.5 \geq 0$

If Item 66/10 > 32.4 in Case 1 or Item 66/100 > 1 in Case 2 then E = 0

S_1 is then calculated as: S1 = 55 - (A+B+C+E) ≥ 0 and ≤ 55

The value of S_1 is used to indicate the overall structural condition, or health, of a bridge, where, S1=55 (New bridge)

Bridge Condition Index, CI = S_1

S1 value ranges between 55 (as-new condition) to 0 (failure).

Geometrics and serviceability

Geometrics and serviceability are measured using the S2 factor, which is calculated based on under-clearance adequacy, waterway adequacy, and roadway width.

Under-clearance Adequacy

If (Item 69 or 9	= 'N'	Then	S2A = 0
8		Then	1
7		Then	2
6		Then	4
5		Then	6
4		Then	8
<= 3		Then	10

Waterway Adequacy

If (Item 71 or 9	= 'N'	Then	S2B = 0
8		Then	1
7		Then	2
6		Then	3
5		Then	4
4		Then	5
<= 3		Then	6

Roadway Width

If Item 43B = 19 or Item 51 = 0, then C = 0

If (Item 51/Item 28)	≤14	Then	S2C = 14
	>14 & ≤15	Then	S2C = 10
	>15 & ≤16	Then	S2C = 6
	>16 & ≤17	Then	S2C = 2
	>17	Then	S2C = 0

S_2 = 30 – (S2A+ S2B+ S2C) ≥ 0

Essentiality for public Use

Essentiality for public is measured based on traffic volume, detour length, and the highway system classification (NHS or non-NHS).

Essentiality for public use

K = (S1 + S2)/85

S3A = (ADT (Item 29) x Detour Length (Item 19) x 15)/(320,000 x K)

NHS Highway

If item 104(Highway System) > 0 Then S3B = 5

Else S3B = 0

S3 = 15 – (S3A + S3B) ≥ 0

Vulnerability and Structure Type Reductions

Structural vulnerability is measured by the S4, which is based on whether the bridge is fracture critical and/or fatigue vulnerable.

If Fracture Critical (Item 92A) then S4A = 2

If Fracture Critical and Fatigue Vulnerable (Item 92C) then S4A = 5

Channel Protection

If (Item 61 or 9	= ‘N’	Then	S4B = 0
8		Then	1
7		Then	2
6		Then	3
5		Then	4
4		Then	5
<= 3		Then	6

S4 = S4A + S4B

Scour and seismic Criticality

Scour and seismic vulnerability are measured using S5. Scour criticality (S5A) is determined based on NBI item 113, where a value less than or equal 3 is considered as "Scour Critical," which would include: (1) bridges with foundations determined to be unstable for calculated scour condition (e.g., scour within limits or within footing base or piles tips; (2) bridges with extensive scour requiring immediate mitigation measures; or (3) bridges where failure of piers/abutments is imminent. In these cases, a reduction of 2 points is assumed.

If Scour Critical (Item 113 <=3)
Then S5A = 2
Else S5A = 0

Seismic vulnerability is determined by Caltrans' Office of Earthquake Engineering, Analysis & Research (OEEAR). The latest screening, completed in 2019, was used in this study to estimate seismic criticality of bridges. OEEAR methodology identifies five categories of seismic vulnerability and calculates hazard and impact score for each bridge. S5B is calculated based on the value of the normalized score provided by OEEAR, as follows.

If Seismic Vulnerability Normalized Score > 0.5 Then S5B = 5
Else if Seismic Vulnerability Normalized Score > 0.2 and <=0.5 Then S5B = 2
Else S5B = 0

S5 = S5A + S5B

The total value of (**S2 + S3 - S4 - S5**) is used to indicate the "criticality index" of a bridge. This index is a surrogate for measuring the impact/consequence of functional inadequacy or failure.

Criticality Index = S2 + S3 - S4 - S5

Criticality index ranges from 0 (highest criticality) to 45 (lowest criticality).

The overall risk index (RI) for a particular bridge is calculated as:

RI = 100 – (CI + Criticality Index)

= 100 – (S1 + S2 + S3 - S4 – S5)

Where, RI ranges from 0 (lowest risk) to 100 (highest risk). A bridge may be considered as low risk (i.e., low priority) if RI<30 and high risk (i.e., high priority for treatment) if RI >= 62.5.

Each of the risk model parameters described above requires a unique predictive model to forecast changes over the life of a bridge, and assess impact of treatments on bridge risk. This process in integrated into the multi-objective optimization model, and is performed systematically over planning horizons, as described in the next section.

A.4 Deterioration Modeling

Bridge deterioration is a complex, multi-dimensional and stochastic process that results from the effects and interaction of several physical and operational factors. Some of the key factors influencing bridge deterioration include the bridge material, structural type, age, truck traffic, total length, number of spans, length of maximum span, skew angle, and bridge location (i.e., exposure to aggressive environmental/climatic conditions such as corrosion). Deterioration models are required to reflect the deterioration rates over time, and correlate bridge physical and operational characteristics with condition ratings to predict the condition of a bridge, or bridge components, at any time during its life.

In spite of numerous research projects addressing this area, the development of reliable deterioration prediction has been, and is still, a major challenge for developing long-range bridge programs. In some cases, the impreciseness and/or incompleteness of the data, combined with the relatively limited knowledge we have about the causal relationships and interdependencies among bridge parameters would make it rather difficult to quantify the impact of various factors on deterioration or to have high confidence in the models. In some cases, the models are still developed based primarily on subjective judgment and expert opinion, with limited use of available inspection data.

In this study, we employed a data-driven approach to develop deterioration models. The approach involved the use of NBI data of Caltrans SHS bridges over 27 years period (1992-2018). In an attempt to correlate bridge physical and operational attributes with condition ratings, the NBI data was examined to identify deterioration patterns and key factors influencing the deterioration process of bridge components. A set of models were then developed to predict condition of each bridge component, as defined in the risk model, at any point in time. The following sub-sections outline the main steps we followed to develop these models.

A.4.1 Data Censoring and Calculation of Average Condition State Waiting Time

To address the above-mentioned data limitations, we implemented an approach to filter (or censor) the 27 years of NBI data to extract bridge records that have not experienced any improvements. Using NBI data between 1992-2018, the condition of each bridge was tracked in each year through the inspection history using the bridge structure number (Item 8). For each bridge, the number of years spent at each condition state, also known as waiting or sojourn time, was calculated. The condition state waiting time concept is often used in calculating transition probabilities in Markov chain models. However, we used it in this study to fit a probability distribution to represent average time of transitioning (or deteriorating) between condition states over the life of a bridge component.

Bridge records that included a condition improvement were excluded, or right censored, to ensure that only age-related deterioration is represented in the data set. Right censoring of the data occurred when a bridge component has undergone a maintenance action that led to improving its condition (i.e., transitioned to a better condition state, where condition at T_{i+1} is better than condition at T_i). For example, a deck condition that transitioned from state 5 to 7.

To illustrate the data extraction and censoring process, Figure 51 shows an example deck condition history for a concrete box girder bridge (Structure number 01 0016).

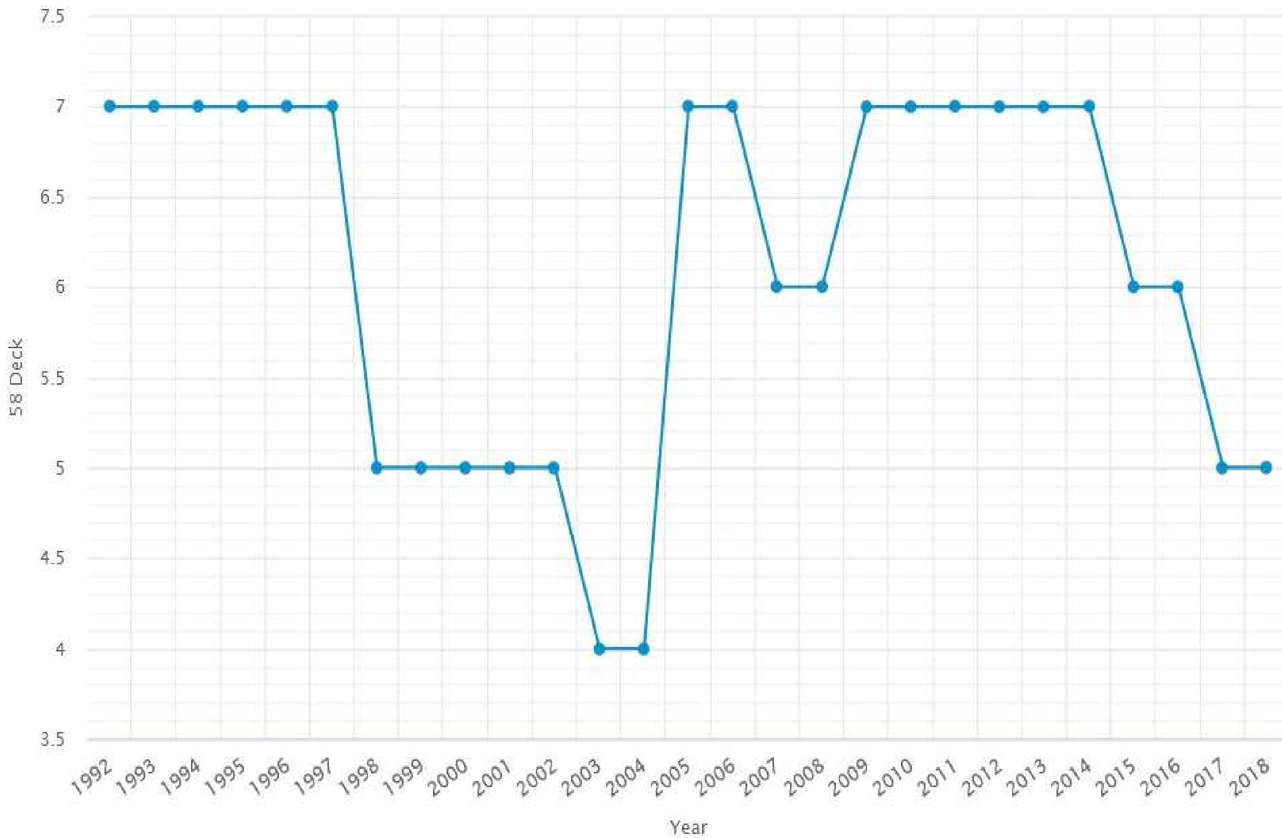


Figure 51: An example deck condition history for a concrete box girder bridge (Structure No. 01 0016)

This typical data trend demonstrates the frequent changes of condition states due to deterioration and improvement actions. However, to be useful for deterioration modeling purposes, this data will need to be right-censored when an improvement has taken place, which appears to have occurred in 2005). It should be noted that we may also choose to left-censor the data if needed (e.g., for issues of data completeness or reliability). However, in our analysis, we chose to start from the first year of recorded NBI data (1992).

For each bridge component, the time spent (or waiting time) in each condition state was calculated. Table 9 shows the historical deck condition ratings of the example bridge (01 0016). Table 10 shows the historical deck condition data after censoring.

Table 9. Historical Deck Condition Rating for an Example Bridge (01 0016)

90 Inspection year	Built Year	Age	..... Other Attributes……	NBI Table Year	58 Deck	Waiting Time
1991	1985	6		1992	7	6
1997	1985	12		1998	5	5
2002	1985	17		2003	4	2
2004	1985	19		2005	7**	2
2006	1985	21		2007	6	2
2008	1985	23		2009	7**	6
2014	1985	29		2015	6	2
2016	1985	31		2017	5	2

** Indicate improvement in condition state

Table 10. Historical Deck Condition Rating for Bridge 01 0016 After Censoring

90 Inspection year	Built Year	Age	...Other Attributes…			58 Deck	Waiting Time
1991	1985	6				7	6
1997	1985	12				5	5
2002	1985	17				4	2

This process was repeated for each bridge component to extract the data that can be used for modeling component deterioration due to aging. For a given component in a specific bridge population (or group), the time spent in one condition state was determined by averaging the waiting time for all bridges in that group, which would represent the average rate of deterioration, where no maintenance actions were performed. Subsequently, a deterioration model for the component in that bridge group can be determined based on the distribution of the cumulative waiting time, assuming the independence between the waiting times in each condition state.

It should be noted that since deterioration is a continuous process, a deterioration model should capture the continuous change in condition over time, and therefore should not approximate the condition to the discrete states for planning purposes. From a modeling perspective, the discrete condition states used in inspections (for practical reasons) would indicate that a component condition would remain static over a number of years, and abruptly change. For developing multi-year plans, the models should capture the continuous deterioration process, from year to year.

A.4.2 Defining Weibull Distribution Parameters

A deterioration model can be defined by the distribution of the cumulative waiting time in various condition states calculated in the previous step. After analyzing distributions of the cumulative waiting time and investigating a number of exponential and polynomial functional forms, we found that a Weibull-based distribution seems to correlate well with historical data and provides reasonable and acceptable predictions with respect to the observed history, and therefore were used to model deterioration of the bridge components. Weibull distribution is commonly used to predict changes of condition (or reliability) over the life of assets.

We used 2-parameter Weibull-based distribution and determined the best fit of the parameters based on examining data distributions and observing the value of the root-mean-square error (RMSE) for each combination of the parameters. The probability distribution function (PDF) and cumulative distribution function (CDF) of a 2-parameter Weibull distribution is given by Equation (1) and (2), respectively:

$$f(x) = \frac{\beta}{\alpha}\left(\frac{x}{\alpha}\right)^{\beta-1} e^{-\left(\frac{x}{\alpha}\right)^{\beta}} \quad x>=0, \text{ where x represents time or asset age} \quad \text{Equation 1}$$

$$f(x) = 1 - e^{-\left(\frac{x}{\alpha}\right)^{\beta}} \quad x>=0 \quad \text{Equation 2}$$

The first parameter, α, is known as the "characteristic life" and is indicates the scale (or spread) in the distribution of data. The second parameter, β, is known as the shape factor and indicates the rate of deterioration.

The median value of the Weibull distribution is given by $\alpha\ (\ln 2)^{\beta}$. The α parameter is analogous to the mean in a normal distribution, and represents the 63.2 percentile of the data. The β parameter represents the rate of deterioration, with an increasing value indicating an increasing rate of deterioration over time. A β value of 3 roughly approximates the rate of a normal distribution, which we found to reasonably reflect the deterioration of bridge components.

The cumulative Weibull distribution function is used to represent the deterioration of individual components in asset groups. The function is scaled to represent the condition ratings used for bridge components (9 to 0 scale for deck, superstructure, and substructure components). Inventory load rating (expressed in metric tons) was mapped to intervals between 0 and 9. These intervals were used to calculate average waiting period. The scaled Weibull function is given in Equation 3.

$$f(x) = 9 - 9 * (1 - e^{-\left(\frac{x}{\alpha}\right)^{\beta}}) \quad x>=0 \quad \text{Equation 3}$$

A.5 Defining Bridge Groups

The censored NBI data of the SHS bridge population was also examined to identify correlation between the condition of bridge components and key deterioration factors. The examined factors include age, (Item 43A) and the type of design and/or construction

(Item 43B), total traffic, truck traffic, design load, total length, maximum span length, and skew angle. This analysis showed that bridge deterioration is primarily influenced by the kind of material (Item 43A) and the type of design and/or construction (Item 43B). Other factors showed weak correlation with condition, and therefore were not considered in defining bridge groups. Some bridge groups showed different deterioration history for interstate and non-interstate bridges.

One approach for developing multivariate deterioration models is to consider condition as a dependent variable and other important deterioration factors as explanatory (independent) variables. However, fitting probability distribution functions for multivariate data, especially for high-dimensional data, may sometimes suffer from a level of inaccuracy which increases with dimensionality, often known as curse of dimensionality. Also, multivariate models may sometimes be difficult to calibrate, where calibrating one variable may negatively impact other variables. Moreover, in cases where data does not show good correlation, or where the preciseness and completeness of data may be in question, the added level of complexity for calibrating multivariate models may not be warranted or practical, given the desired, and feasible, level of predictive accuracy needed for developing long-term asset management plans.

In this study, we employed an approach, to reduce the problem dimensionality from multivariate to univariate, by categorizing bridges into a set of groups (or cohorts) that are assumed to have general homogeneous characteristics in terms of their deterioration rate and/or criticality. The grouping is based on the main factors determined to be influential in determining the rate of deterioration.

For each defined group, univariate deterioration models, where age is used as the only independent variable, were developed based on the cumulative average waiting times calculated previously. It should be noted that this approach can be extended to include more explanatory variables, if needed. However, the objective is to keep the number of these variables to the minimum, for the reasons mentioned above. It is also worth noting that it is important to define groups at an appropriate level of granularity to balance the level of desired accuracy in predicting deterioration and criticality, with the time and effort needed to build group-specific models.

Analysis of the SHS bridge population showed that bridge deterioration factors are primarily influenced by the kind of material (Item 43A) and the type of design and/or construction (Item 43B). Some of the groups showed different deterioration pattern for interstate and non-interstate bridges, and therefore, they were grouped further. In total, 24 groups were defined, as shown in Table 11.

Table 11. Definition of SHS Bridge Groups

Group ID	Bridge Type	Number of Bridges	Total Deck Area (sq. ft)
N-Slab-Conc-Cont	Non-Interstate Slab -Concrete (Continuous)	868	5,692,617
I-Slab-Conc-Cont	Interstate Slab -Concrete (Continuous)	568	3,576,307
Slab-Conc-S	Slab -Concrete (Simple)	301	1,443,969
Slab-PC-Cont	Slab -Prestressed Concrete (Continuous)	39	427,180
Slab-PC-S	Slab-Prestressed Concrete (Simple)	82	514,336
Box-Single-PC-C	Box Girder (Single)-Prestressed Concrete (Continuous)	105	3,691,740
Box-Single-PC-S	Box Girder (Single)-Prestressed Concrete (Simple)	49	393,241
Box-Single-Conc	Box Girder (Single)-Concrete	51	1,041,622
I-Box-Multiple-PC-C	Interstate Box Girder (Multiple)- Prestressed (Continuous)	498	24,448,585
N-Box-Multiple-PC-C	Non-Interstate Box Girder (Multiple)- Prestressed (Continuous)	1878	54,545,773
N-Box-Multiple-PC-S	Non-Interstate Box Girder (Multiple)- Prestressed (Simple)	802	8,308,183
I-Box-Multiple-PC-S	Interstate Box Girder (Multiple)- Prestressed (Simple)	463	5,702,563
N-Box-Multiple-Conc-Cont	Non-Interstate Box Girder (Multiple)-Concrete (Continuous)	1708	33,365,117
I-Box-Multiple-Conc-Cont	Interstate Box Girder (Multiple)- Concrete (Continuous)	939	30,144,044
Box-Multiple-Conc-S	Box Girder (Multiple)- Concrete (Simple)	437	4,673,697
TBeam-PC	T-Beam Prestressed Concrete (Simple & Continuous)	54	3,267,681
TBeam-Conc-S	T-Beam Concrete (Simple)	197	1,243,511
N-TBeam-Conc-Cont	Non-Interstate T-Beam Concrete (Continuous)	701	7,066,275
I-TBeam-Conc-Cont	Interstate T-Beam Concrete (Continuous)	318	5,479,382
Stringer-PC-Cont	Stringer Prestressed Concrete (Continuous)	225	4,681,317
Stringer-PC-S	Stringer Prestressed Concrete (Simple)	281	5,677,622
Stringer-Steel-Cont	Stringer Steel (Continuous)	138	4,752,478
Stringer-Steel-S	Stringer Steel (Simple)	433	12,212,511
Stringer-Conc	Stringer Concrete	50	2,299,298
TOTAL		**11,185**	**224,649,050**

According to the proposed risk model, predicting a bridge condition index would require the prediction of each of the four components, which include: deck condition, superstructure condition, substructure condition, and load capacity reduction. Therefore, a total of four deterioration models are required for each bridge group (i.e., 96 models for the 24 groups). Figure 52 shows the total number and percentage of each group of the SHS bridge inventory.

The defined 24 groups represent approximately 98% of the total number, and 92% of the total deck area of Caltrans SHS bridges. The remaining 273 bridges were found to require special modeling due to their limited number and/or unique structure. Classified by the type of design/construction (Item 43B), these bridges include: 31 Frame, 3 Orthotropic, 8 Truss0Deck, 22 Truss-Thru, 102 Arch-Deck, 7 Arch-Thru, 5 suspension, 9 segmental box girder, 33 Girder/Floor-beam system, 12 Channel Beam, and 15 movable bridges. Further analysis is required to model these bridges.

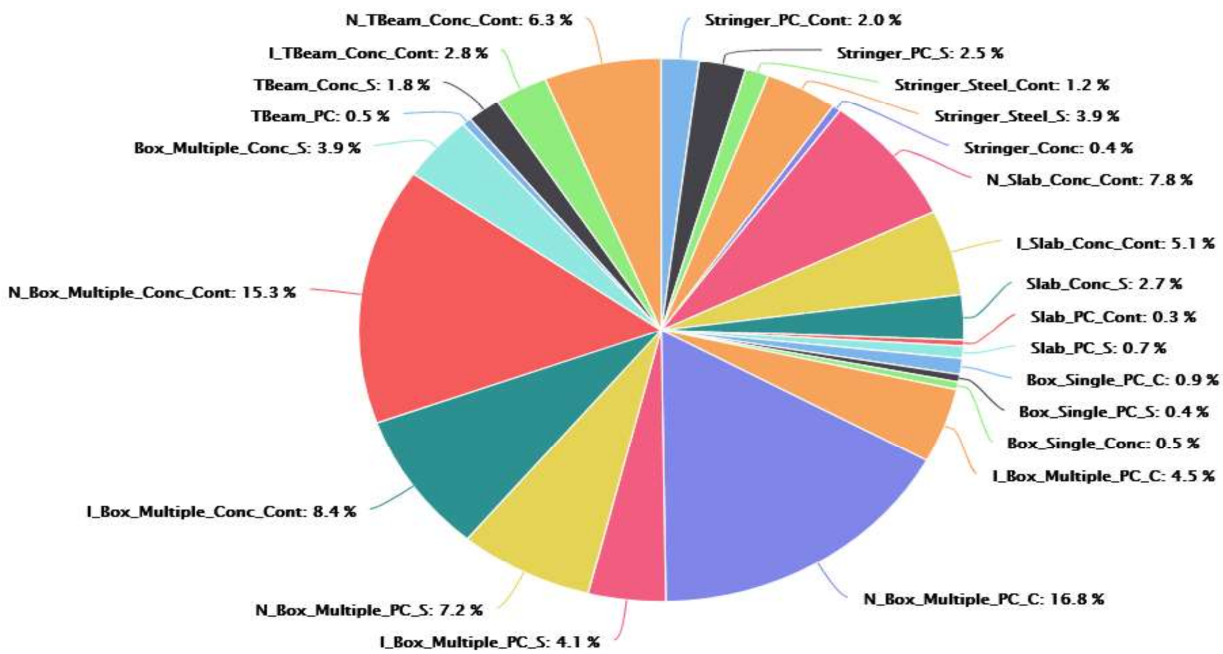


Figure 52: Number of bridges in the defined 24 groups as % of SHS bridge inventory

A.6 Defining Deterioration models for Bridge Groups

Weibull-based deterioration models were developed for each bridge component, in each of the 24 defined groups. The Weibull parameters were defined to ensure a best fit (i.e., lowest RMSE) with the condition state cumulative waiting time series. The example below explains the process used to develop the Weibull models for all 24 groups. This example shows the development of the deck deterioration model for the non-interstate box girder continuous concrete bridges. Figure 53 below shows the average waiting times calculated for each deck condition state using the set of right-censored data for that group. Table 12 shows the calculated waiting times and cumulative waiting times in each deck condition state for the same group.

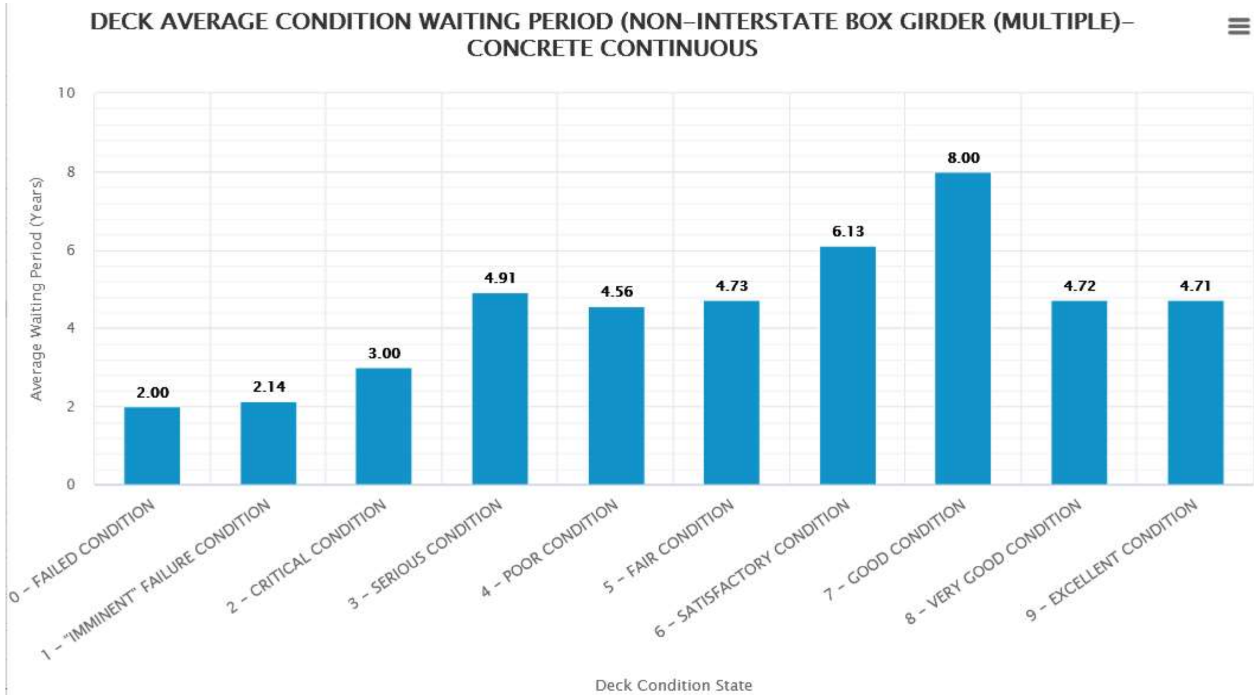


Figure 53: Average waiting times in each condition state of the deck component in the non-interstate box girder (multiple) continuous concrete bridges

Table 12. Deck condition waiting times in the example group

Condition Rating	Year in This Condition	Cumulative Number of Years
9	4.71	4.71
8	4.72	9.43
7	8	17.43
6	6.13	23.56
5	4.73	28.29
4	4.56	32.85
3	4.91	37.76
2	3	40.76
1	2.12	42.88
0	2	Infinity

Different distributions (e.g., exponential, polynomial, linear, etc.) or Weibull distribution (Figure 54) can be fitted on the calculated cumulative waiting time.

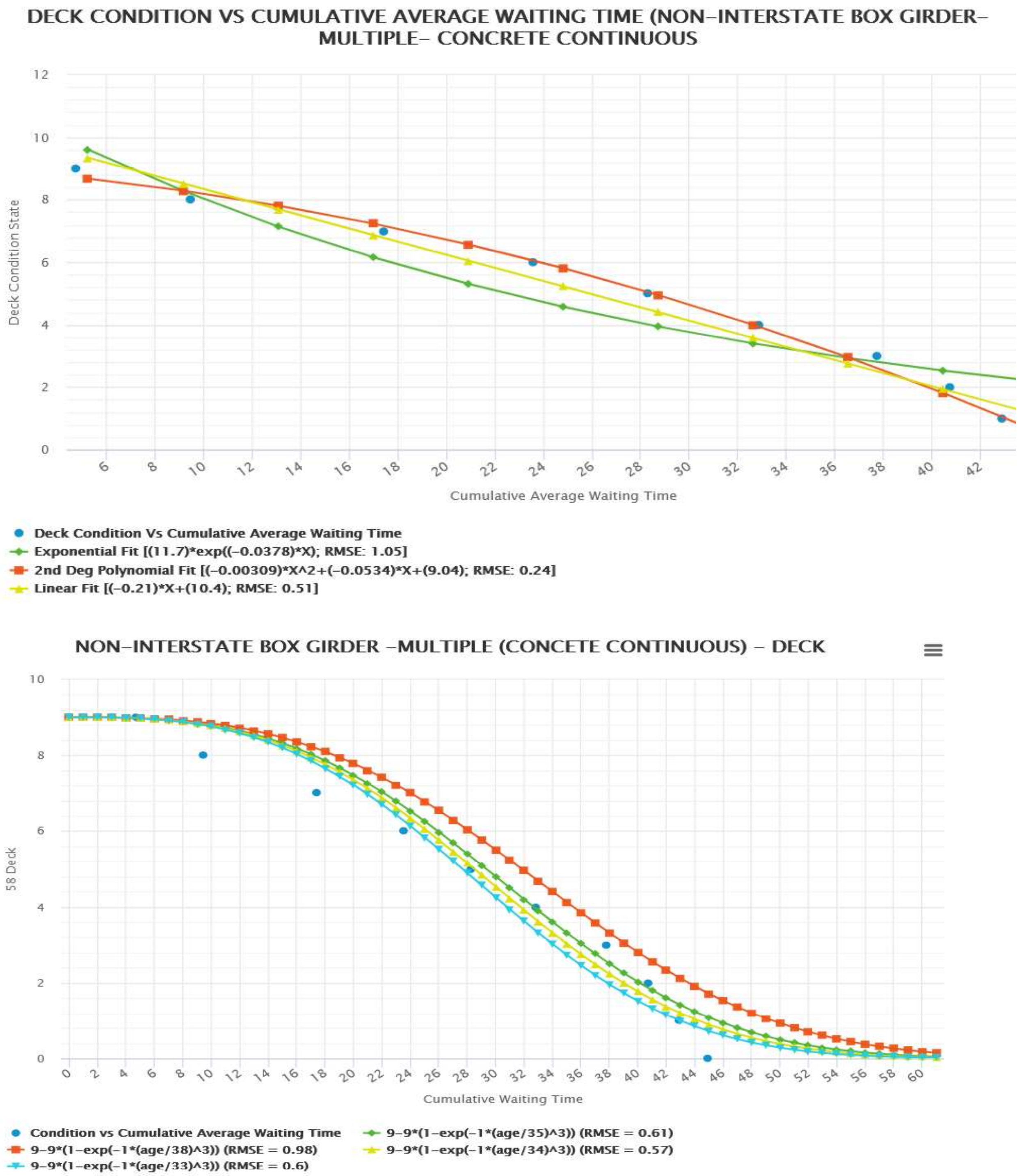


Figure 54: Fitting different distributions for the cumulative average waiting times

By examining the goodness of fit of these distributions (measured by the root-mean-square error), the best Weibull parameters can be defined for each component in each group, as shown in Figure 55. Table 13 provides the best values of the Weibull parameter (α) for the deck, superstructure, and substructure components for each of the defined 24 groups.

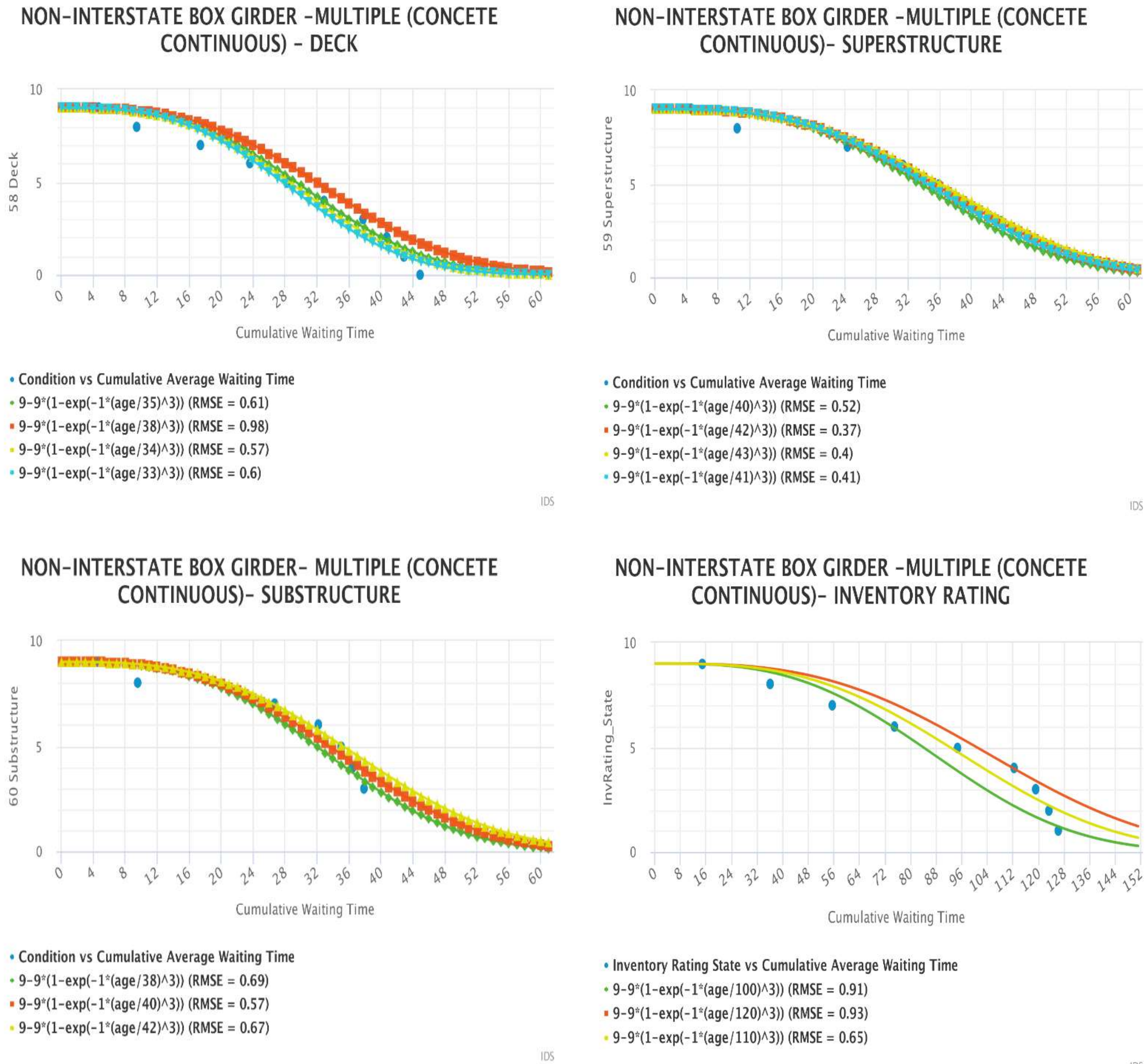
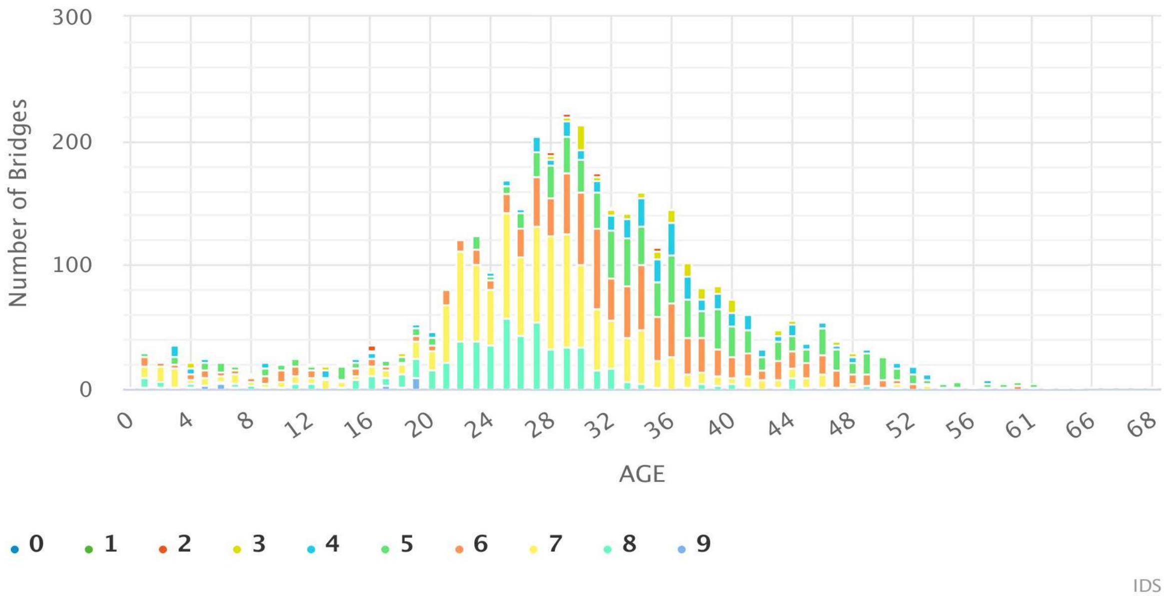


Figure 55: Examining Weibull parameters and goodness of fit for each model

Table 13. Characteristic Life Parameter (α) for the 24 Groups Weibull Models

Group ID	Deck	Superstructure	Substructure
N-Slab-Conc-Cont	38	40	38
I-Slab-Conc-Cont	30	33	40
Slab-Conc-S	34	35	40
Slab-PC-Cont	22	20	23
Slab-PC-S	34	35	36
Box-Single-PC-C	16	15	15
Box-Single-PC-S	18	20	20
Box-Single-Conc	23	29	24
I-Box-Multiple-PC-C	32	36	37
N-Box-Multiple-PC-C	31	32	37
N-Box-Multiple-PC-S	35	37	42
I-Box-Multiple-PC-S	35	38	42
N-Box-Multiple-Conc-Cont	34	42	40
I-Box-Multiple-Conc-Cont	32	40	40
Box-Multiple-Conc-S	30	32	32
TBeam-PC	33	49	35
TBeam-Conc-S	30	37	34
N-TBeam-Conc-Cont	34	40	40
I-TBeam-Conc-Cont	33	36	36
Stringer-PC-Cont	32	37	40
Stringer-PC-S	33	42	42
Stringer-Steel-Cont	27	37	37
Stringer-Steel-S	36	41	43
Stringer-Conc	23	23	12

The censored data and selected distribution parameters showed a consistent behavior and reasonable correlation for almost all of the groups, especially when sufficient data points were available, in spite of the presence of outliers. Figure 56 shows an example frequency chart of deck condition and age for censored data of the non-interstate box girder concrete continuous group, which is consistent with our observations and understanding of average life and deterioration of decks for this type of bridges. Figure 56 also shows the distribution of the condition and age data for the entire population in this group, indicating a reasonable correlation with age



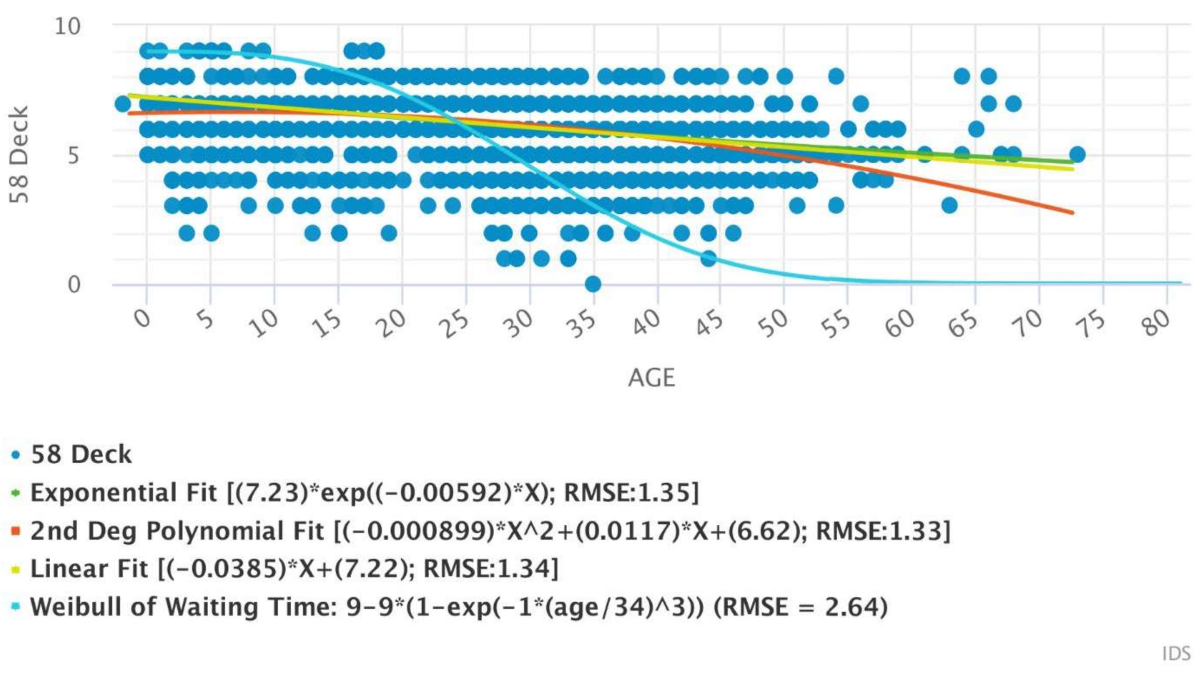


Figure 56: Deck condition distribution with age for the non-interstate box girder (multiple) continuous concrete group, using censored data and assumed Weibull distribution

A.7 Condition Predictions Using Incremental Models

A defined deterioration model is assumed to represent an average distribution (or deterioration trend) of a specific bridge component in a specific group. However, in reality, individual components within a particular group are rarely identical and often deteriorate at different rates due to a wide range of factors, including the factors we described above, which would cause these components with identical age to be at different condition states, as shown in Figure 57. Therefore, predicting the condition of a particular component should always take into consideration its initial condition state.

Although the vast majority of the differences between initial condition states within a single group may occur due to different physical, operational, or environmental factors, some outliers may also be attributed to limitations or inconsistencies in data recording. For example, the outliers shown to the right in Figure 57 indicate deck condition state of 7 or 8 for bridges with more than 60 years of age. These decks were likely replaced at some point; however, the recorded data have not captured the deck replacement year, where age is calculated based on the original construction year of the entire bridge structure. On the other hand, some outliers (to the left in Figure 57) show decks in condition states 2, 3, 4, or 5, while being less than 10 years old. This may also indicate data discrepancy where the bridge construction (or reconstruction) year may have been updated due to the replacement or major rehabilitation of another bridge component (e.g., bridge superstructure or substructure).

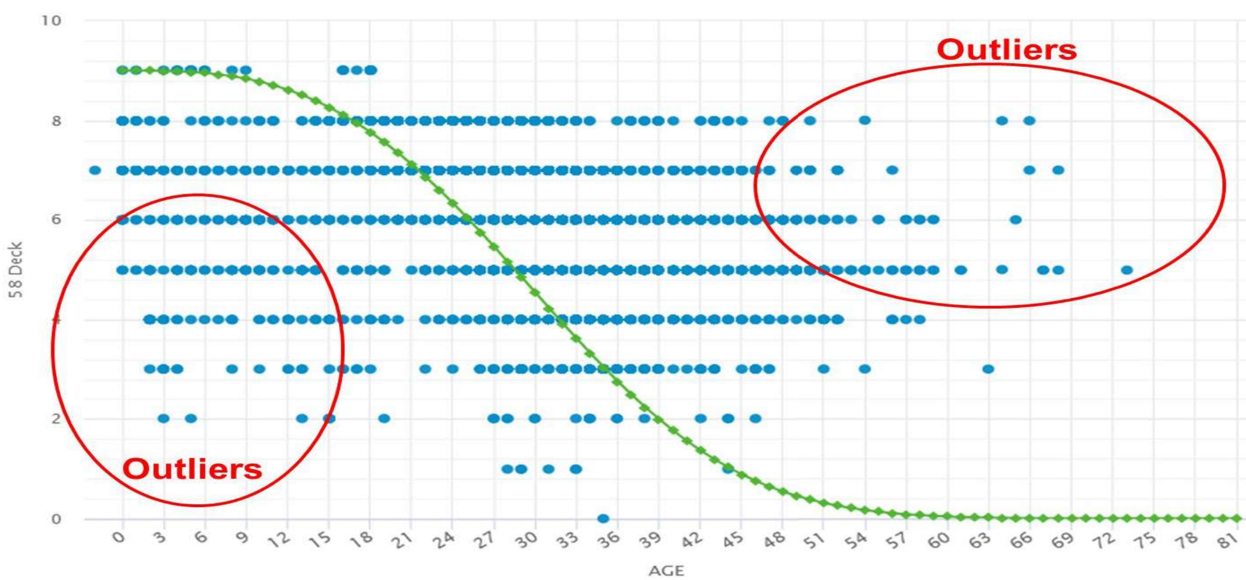


Figure 57: Distribution of initial deck condition ratings with respect to defined Weibull model for the non-interstate concrete box girder bridges (multiple-continuous)

Data discrepancy and presence of outliers are commonly found in practice, especially when considering large bridge inventories in NBI data. In our proposed approach, we examine the extent of these outliers, and if they are found to represent a significant portion of a group population, this would indicate the need to define a separate group for these bridges. Otherwise, the defined models should define a special case for dealing with these bridges (e.g., assuming another distribution for the outliers).

The defined deterioration models were used predict the change in a bridge component condition starting from an initial state, as a function of age (independent variable). The initial condition state for each component were set to the values recorded in 2018 NBI data. Starting from an initial state, the models are used in an incremental recursive manner to predict future values, where the value in a specific year would be calculated based on the initial value known at a previous year. Since inspection cycles may occur at varying times, the initial values may also be captured at different inspection years. Figure 58 shows an illustration of this incremental analysis. The curve defined in Figure 58 is a zoomed-in part of the Weibull model in Figure 57.

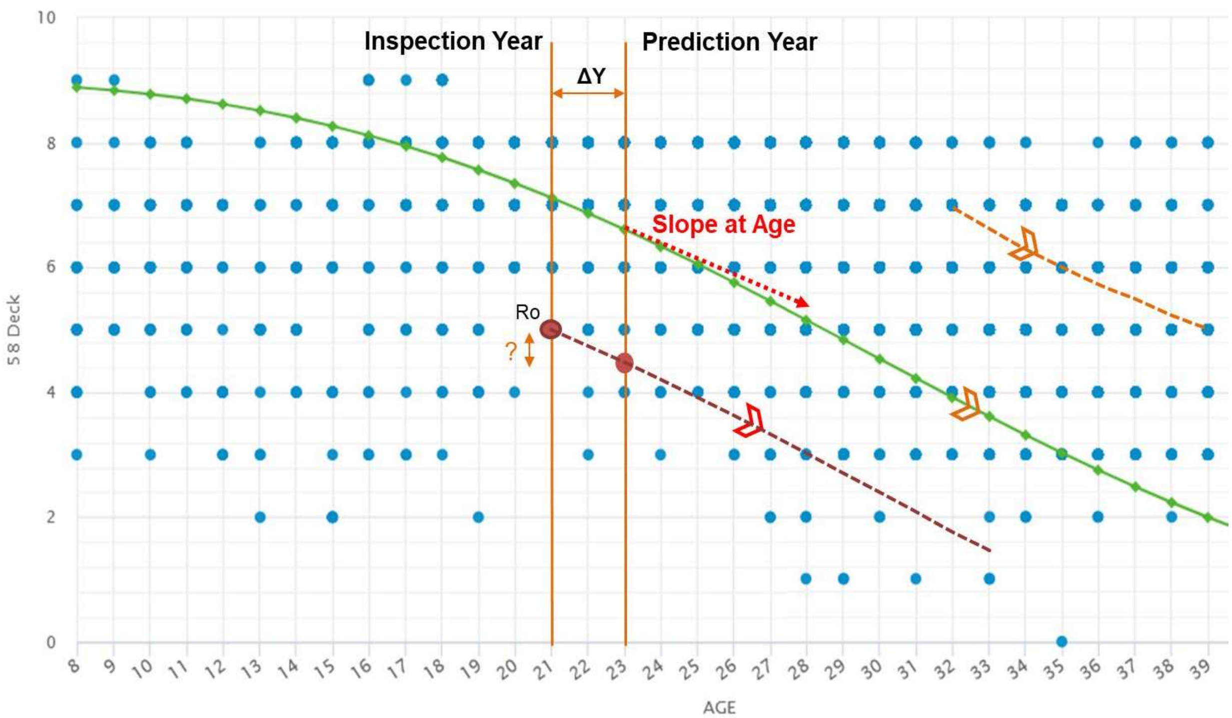


Figure 58: Using the deterioration models to predict future condition states starting from initial states using an incremental recursive approach

The example in Figure 58 shows the calculation of the deck condition state at a future year when the bridge age is x (i.e., R_x), given an initial value (R_o) at the last inspection (or predicted) year. The predicted value can be calculated as shown in Equation 4.

$R_x = R_o - \Delta Y * \frac{d}{dx} f(x)$ Equation 4

Where,

R_x = Predicted condition at age x

R_o = Initial value

ΔY = Number of years between prediction year and the year of the initial value

$\frac{d}{dx}\ f(x)$ = Slope of the Weibull function $f(x)$ at age x

The slope (or derivative) of the Weibull cumulative distribution is given by Equation 5

$$f'(x) = \frac{9\beta}{\alpha^{\beta}} * x^{\beta-1} e^{-\left(\frac{x}{\alpha}\right)^{\beta}} \qquad \text{Equation 5}$$

To validate the developed 96 deterioration models, future condition was predicted over a 20-year period (2020-2040) for all components in all groups, starting from the initial states in 2018 NBI data. Figure 59 shows the historical vs predicted values for three example bridges.

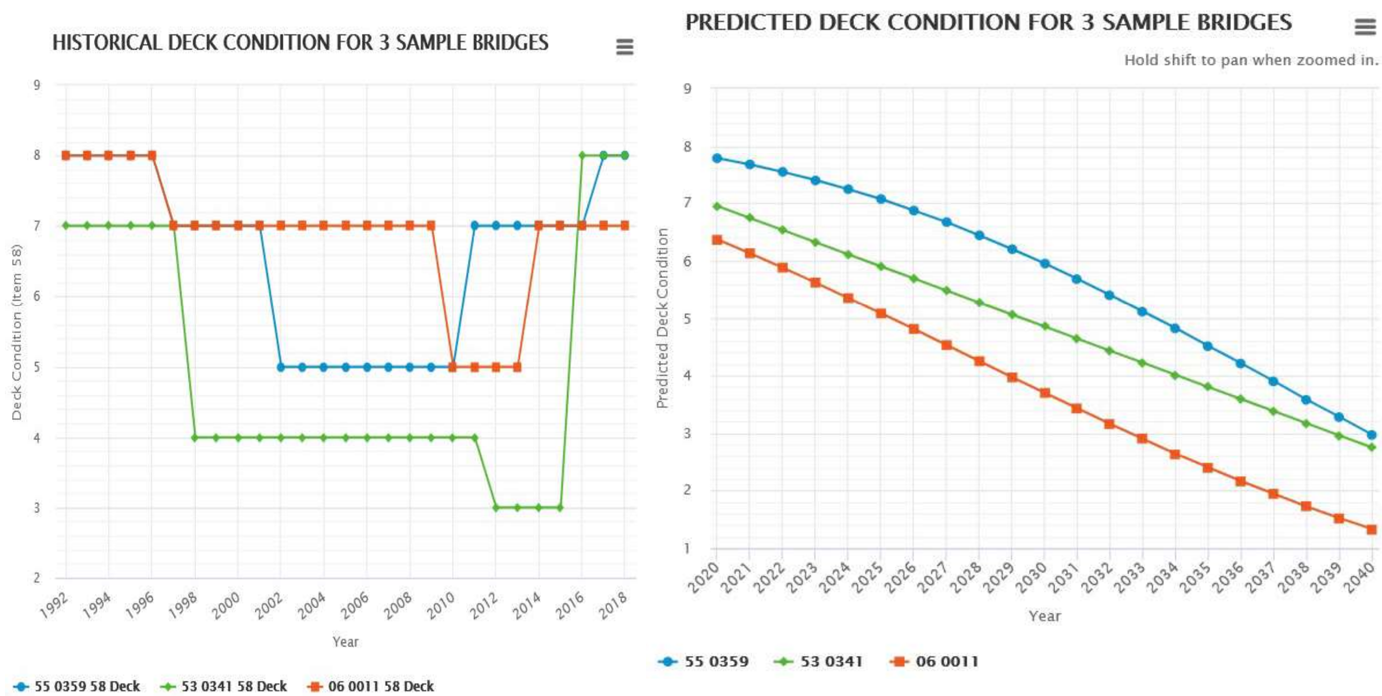
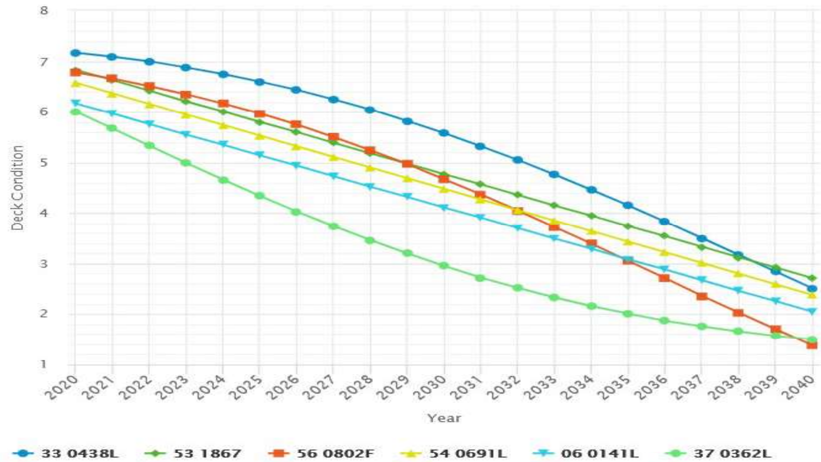
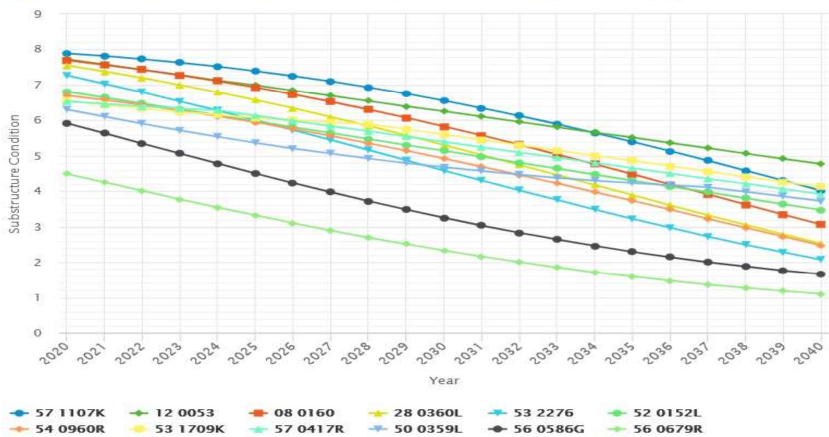


Figure 59: An example showing historical vs predicted deck condition for three sample bridges

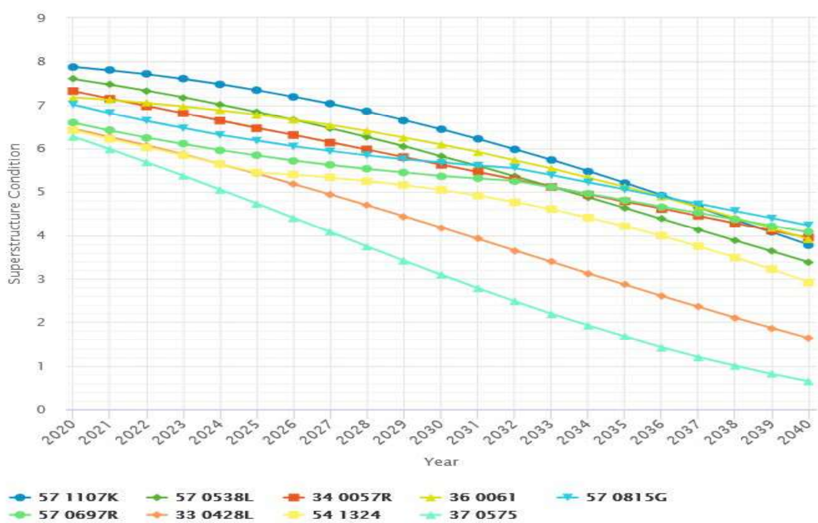
Figure 60 shows 20-year predictions of deck, superstructure, and substructure conditions for a sample of bridges. Figure 61 also shows example predictions of the overall condition index (CI, or S1) and risk index (RI) for some bridges.



Example Predictions of Deck Condition

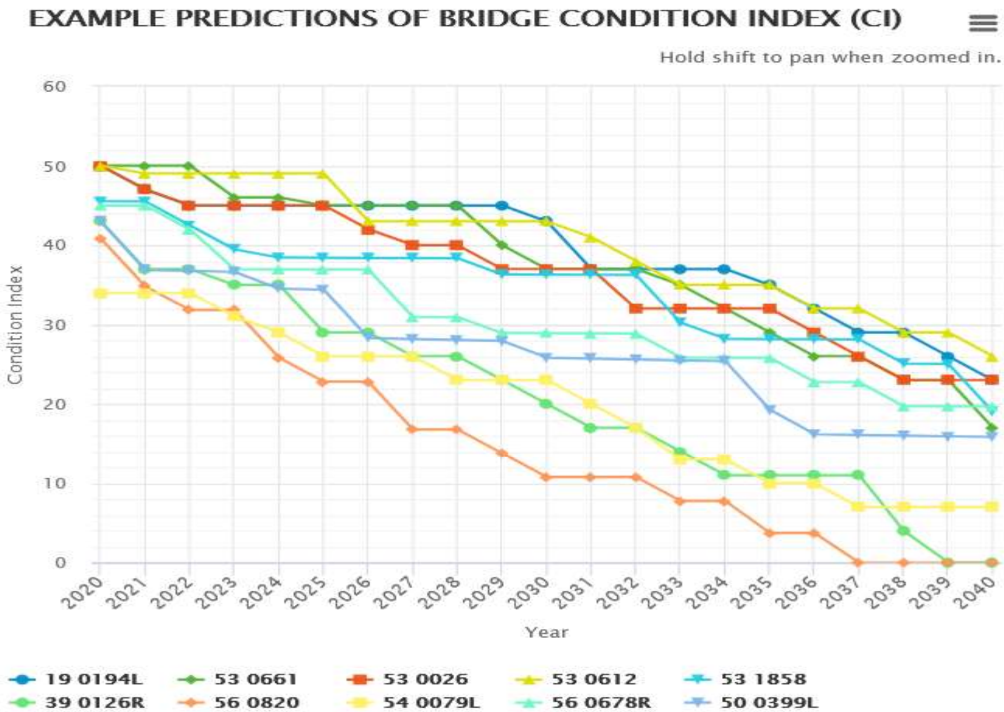


Example Predictions of Substructure Condition



Example Predictions of Superstructure Condition

Figure 60: 20-Year predictions of deck, superstructure, and substructure conditions for some bridges



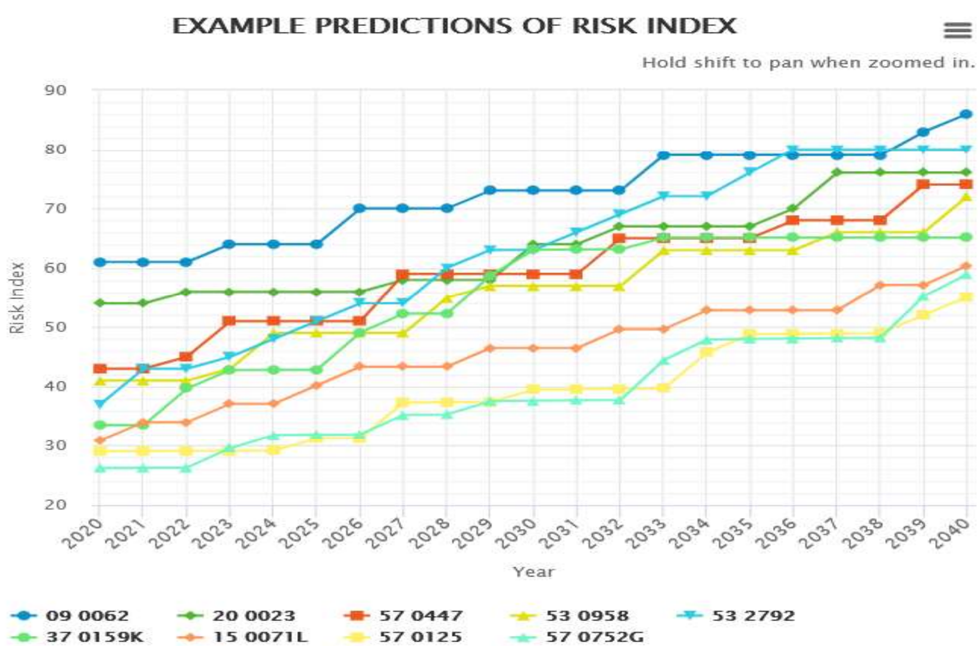


Figure 61: Example prediction of Condition Index and Risk Index for some bridges

The developed deterioration models may also help in assessing the benefit of maintenance and preservation for a given group of bridges. For example, the curves in Figure 62 show the best fit of a Weibull model for the current (2018) deck condition data of the box girder (multiple) simple concrete bridges (shown in green), and the model developed for the censored data set of the same group (shown in red). It can be seen that for this bridge group, the deck maintenance/preservation actions significantly extended the service life of the deck.

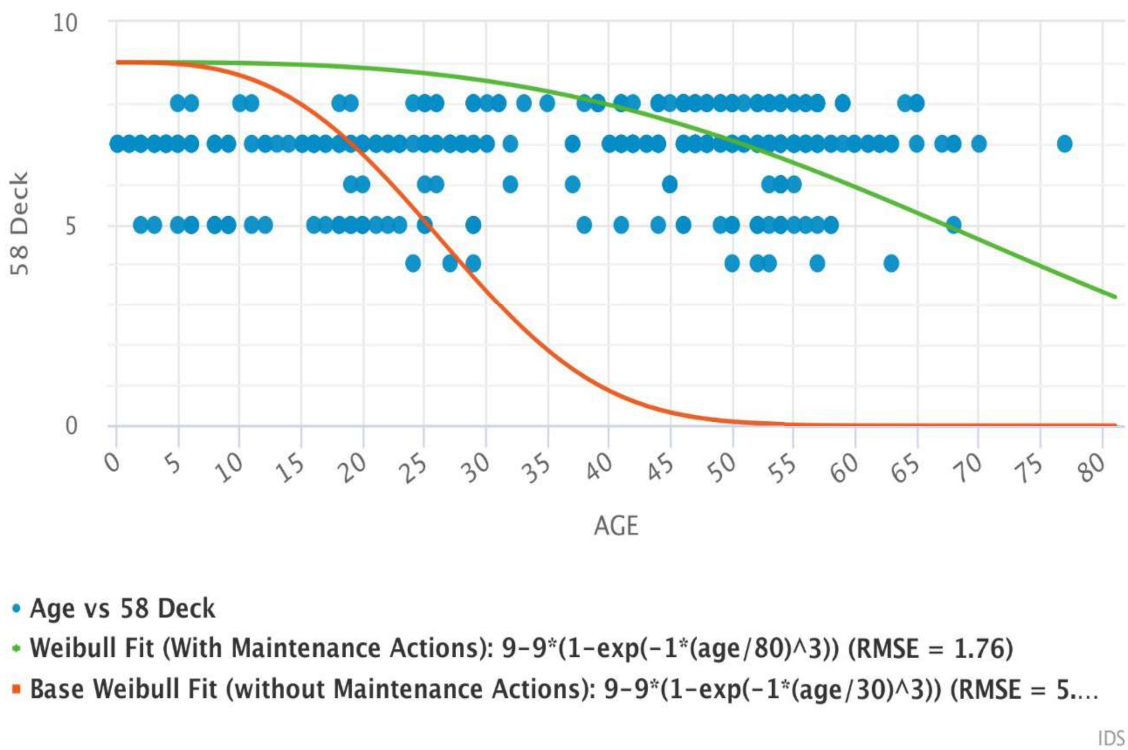


Figure 62: Deterioration models help show the Impact of historical maintenance/preservation actions

A.8 Bridge Treatments Models

During the optimization process, and in each year in the planning horizon, candidate improvement treatments are evaluated for each bridge, based on applicability constraints, as well as cost and benefit models defined for each treatment. The range of treatments that can be defined in the model includes various preservation, rehabilitation, functional improvement, or replacement actions. The treatment selection technique will ensure feasibility and achieving the best cost-benefit trade-offs.

In this study, six treatments were defined along with a set of constraints to reflect some common rules and work practices. The current treatments include: concrete overlay, deck repair, deck replacement, bridge replacement, bridge widening, and prestressed beam end repair. The list of treatments can be easily extended to include others used at Caltrans.

Cost and effectiveness models for each treatment were used to estimate expected total cost and impact when the treatment is applied on a specific bridge. Approximate unit costs for these treatments were estimated using published Caltrans documents or based on previous experience and other data sources. Expected improvements for each of these treatments were also assumed, along with a set of rules governing the applicability of each treatment.

In developing cost and effectiveness models, judgement was made to determine what would normally be repaired during a bridge deck repair or rehab project. For example, during a deck overlay project, it was assumed that the superstructure or substructure would also have minor repairs done if their condition ratings were below a given threshold. Similarly, it was assumed that during a deck replacement project, some repairs would also be performed on the superstructure or substructure.

Treatments models also involves the definition of applicability constraints to ensure the technical feasibility and cost-effectiveness of a treatment when it is used on a particular bridge. Several applicability constraints were defined based on NBI attributes. Examples of used NBI attributes to define the constraints include: NBI Item 43A (material), Item 58 (deck condition), Item 59 (superstructure condition), Item 60 (substructure condition), Item 64 (operating rating), Item 108A (wearing surface), Item 68 (deck geometry), and the composite bridge condition index. For instance, constraints on the applicability of concrete overlay to a given bridge specified that: Item 43A = 1,2,3,4, or 5; Item 58 = 4,5, or 6; Item 59 > 4; Item 60 > 4; Item 64 > 32.4 tons; Item 68 > 3; and Bridge Condition Index > 30.

It is worth noting that while some of these criteria (e.g., material) were static, other criteria (e.g., deck or superstructure condition) were time-dependent, where the application of the constraints over the planning horizon will be based on predictions of future values calculated by the defined deterioration models. Table 14 summarizes the rules used to define the applicability constraints of treatments.

Table 14. Treatments' applicability criteria

Treatment	Material (43A)	Deck CI (58)	Super CI (59)	Sub CI (60)	Operating Rating (64)	Wearing Surface (108A)	Deck Protection (108C)	Deck Geometry (68)	Condition Index (S1)
Concrete Overlay	1,2,3,4,5, 6	4-6	>=5	>=5	>32.4 tons	1,4	0,1,2	>3	>30
Deck Replacement	1,2,3,4,5, 6	<=5	>=5	>=5	>32.4 tons	Any	Any	>3	>20

Treatment	Material (43A)	Deck CI (58)	Super CI (59)	Sub CI (60)	Operating Rating (64)	Wearing Surface (108A)	Deck Protection (108C)	Deck Geometry (68)	Condition Index (S1)
Deck Repair	1,2,3,4,5,6	4-5	>=4	>=4	Any	Any	0,1	Any	>25
Bridge Replacement	1,2,3,4,5,6	<=6	<=6	<=6	Any	Any	Any	<=5	<30
		<=6	<=5	<=6				Any	
		<=6	<=6	<=5				Any	
		<=5	<=6	<=6				Any	
Bridge Widening	3,4,5,6	>4	>4	>4	>32.4 tons	Any	Any	2	>25
Prestressed Beam End Repair	5 (43B = 2,3)	>=4	<5	>=4	Any	Any	Any	Any	>30

Treatments' effectiveness are defined in terms of incremental condition improvement. Examples of improvements include higher condition ratings for bridge components, improved load rating, or improved bridge geometrics. The improvements often depend on a number of factors including the physical characteristics of the bridge and the current condition rating. Some constraints may be defined to specify a maximum limit to condition improvement for any treatment. For example, the condition rating of a bridge deck (NBI Item 58) was assumed to improve by 3 points as a result of an overlay, while the maximum improved condition can be capped at 7.

Another set of constraints were defined where the application of a specific treatment may be dependent on prior treatments applied over the planning horizon. These constraints may lead to eliminating future application of specific treatments depending on prior treatments made over the planning horizon. For example, a constraint may eliminate the use of repair on a deck for 10 years after a deck overlay treatment. Another set of constraints may specify the maximum number of occurrences of a particular treatment (e.g., deck repair should only be applied for two times on the same deck over the planning horizon, after which an overlay or deck replacement should be used). Table 15 summarizes the unit costs and condition improvement for each of the defined treatments, and a set of constraints that govern future applications of other treatments if a given treatment is used.

Table 15. Unit costs, improvements, and some rules used in the proposed model

Treatment	Unit Cost	Expected Improvements (Effectiveness)	Rules
Concrete Overlay	$50/sq. ft ($538/Sq. m.)	3 points increase in Deck with a maximum deck condition rating of 7, increase superstructure and substructure by 1 point with a maximum condition rating of 7.	Do not re-overlay or replace or re-deck for 15 years. Do not repair deck for 5 years.
Deck Replacement	$230/sq. ft ($2,476/Sq. m)	Reset deck to condition 8, superstructure to condition 7, and substructure to condition 7.	Do not replace bridge for 15 years
Deck Repair	$8/sq. ft ($86/Sq. m)	2 points increase in deck condition.	Only repair deck twice. After second repair, deck should be overlaid or replaced. Do not repair, overlay, or replace deck for 5 years.
Bridge Replacement	$635 sq. ft ($6,835/Sq. m)	Reset all performance variables to As-New (Deck CI, Super CI, Sub CI, Inventory Rating, Items 69, 71, 61, 51, 92A, 92C, 113, and Seismic Score). Also, reset reconstruction year to year of replacement.	
Bridge Widening (Adding 12' Lane)	$225/sq. ft of New Deck Width ($2,422 * 3.6576 * Structure Length in meters)	2 points increase in Deck with a maximum rating of 8, Superstructure to condition 7, Substructure to condition 7.	Do not replace deck or bridge for 20 years.
Prestressed Beam End Repair	$3000/Beam End* (See note below)	Superstructure increase 2 points to a maximum of 7, Substructure to condition 7	Do not repair beam ends for 15 years. Do not replace bridge for 10 years. Do not replace overlay deck for 5 years.

* The cost of prestressed beam end repair is calculated based on the number of beam ends, and assuming 6 feet beam spacing in the cross section (i.e., bridge width divided by 6 feet). The total cost of beam end repair projects is calculated by multiplying the unit cost ($3,000/beam end) by the number of beams by the number of joints, where the number of joints is assumed to be 2 if the total bridge length (Item 49) is <= 450 feet (137.16 meter), otherwise the number of joints is assumed to be 4.

A.9 System-Level Condition and Risk Metrics

The optimization objective function used for project selection is formulated to maximize system-level condition or minimize system-level risk index at the lowest lifecycle cost. These two system-level measures are calculated using a weighted average value based on deck area to represent the overall system condition and risk levels. System-level weighted average condition index (WACI) and risk index (WARI) are calculated as shown in Equations 6 and 7, respectively.

$$WACI \ = \frac{\sum_{i=0}^{N} \ CI_i \ \ DeckArea_i}{\sum_{i=0}^{N} DeckArea_i} \qquad \text{Equation 6}$$

$$WARI \ = \frac{\sum_{i=0}^{N} \ RI_i \ \ DeckArea_i}{\sum_{i=0}^{N} DeckArea_i} \qquad \text{Equation 7}$$

Where,

$WACI$ = System-level weighted-average condition index

$WARI$ = System-level weighted-average risk index

$DeckArea_i$ = Deck area of Bridge i

CI_i = Condition index of Bridge i

RI_i = Risk index of Bridge i

N = Number of bridges considered in scenario

The multi-objective optimization model stochastically searches all possible combinations of bridges and feasible treatments to find a set of optimal solutions, each representing a candidate annual project list. The cost, benefit, and applicability rules of treatments are evaluated, as described below, to identify the optimal solutions. A subset of the solutions that satisfy financial constraints and condition and risk targets are then selected for further evaluation and trade-off analysis. The selected project list is then applied to update the condition of the bridges for the following planning period. In multi-year planning scenarios, this process is repeated for every year in the planning horizon. Resulting project lists are then used to quantify relationships between funding levels and the defined system-wide performance and risk measures.

A.10 Preliminary Planning Scenarios and Trade-off Analysis

Based on the lifecycle and treatments models described in previous sections, we defined initial planning scenarios to assess the validity and accuracy of these models, investigate the impact of varying budget levels, and estimate the financial requirements for maintaining the SHS bridge inventory over the next 10 or 20 years. These initial scenarios will be revised to align with Caltrans estimated funding and performance targets.

Two sets of preliminary scenarios were defined and used to determine annual project lists over 10- and 20-years planning horizon. The two sets include: (1) Budget scenarios to assess the impact on system-level condition and risk levels; and (2) Target scenarios to evaluate budget requirements to achieve certain system-level performance and risk objectives.

The preliminary scenarios include:

(1) Two baseline Do-Nothing scenarios, to determine the impact of zero investment over 10- and 20-years (2020-2030, 2020-2040).
(2) Four 10-year budget scenarios (2020-2030), assuming fixed annual investment levels: $500 million, $800 million, $1 billion, and $2 billion.
(3) Two 10-year budget scenarios (2020-2030), assuming stepped annual budget that increases over the years: $1 to $2 billion, and $800 million to $2.5 billion.
(4) Two 20-year budget scenarios (2020-2040). One of the scenarios assumed a fix annual budget of $1 billion, and the second assumed a stepped budget from $800 million to $5 billion.
(5) Two condition target scenarios to assess financial requirements to maintain status quo system-level condition index of 43, over 10- and 20-years (2020-2030, 2020-2040), assuming unlimited budget.
(6) Two risk target scenarios to assess financial requirements to maintain status quo system-level risk index of 32, over 10- and 20-years (2020-2030, 2020-2040), assuming unlimited budget.
(7) One risk target scenario to assess financial requirements to maintain status quo system-level risk index of 32, over 10-years (2020-2030), assuming a maximum possible budget of $2.5 billion.

Some constraints were assumed on the budget splitting among different types of treatments. These constraints can be modified to reflect Caltrans current practices, or to investigate the impact of a specific budget splitting regime. For example, some scenarios can be developed to assess the impact of a preservation-focused plan versus a replacement-focused plan. For example, Table 16 shows some budget splitting assumptions used in some scenarios.

Table 16. Example budget splitting limits assumed for some scenarios

Treatment	Maximum annual Investment as % of Total Annual Budget	Maximum number of projects
Bridge Replacement	60%	
Deck Replacement	25%	
Concrete Overlay	15%	
Deck Repair	10%	500
Bridge Widening	10%	
Prestressed Beam End Repair	10%	

An average annual inflation rate was assumed to be 4% for all scenarios.

Details of the annual project lists generated in each scenario are included as Excel sheets in appendix A. IDS Asset Optimizer software may also be used to support analysis and interactive visualization of scenario results.

Scenario results show future condition and risk trends (in terms of system-level average condition and risk indices), detailed information on condition and risk attributes of each bridge and bridge component, as well as annual cost and work type of projects. Results from these scenarios were used to investigate budget implications as well as to assess level of investment requirements to meet status-quo condition and risk levels. The impact of each scenario on system-wide condition and risk levels was assessed and compared with other scenarios.

For example, Figure 63 and Figure 64 show a summary of the $800 million scenario. Figure 63 shows the system weighted-average condition and risk indices over the 10-year planning horizon. It also shows the number of cost of projects for each treatment, Figure 64 shows the weighted-average condition index for the deck, superstructure, and substructure components. It also shows the distribution of the condition states of each component over the 10-year planning horizon. Information on selected projects can also be accessed using the GIS interface in Asset Optimizer (Figure 65). Comparison between different scenarios provided an insight on the trade-offs between different investment levels. For example, Figure 66 shows a comparison between four budgets scenarios: Do-Nothing, $500 million, $800 million, and $1 billion.

Figure 63. Example results of the $800 million scenario showing average condition index (top-left), average risk index (top-right), number of projects (bottom-left), and cost of projects.

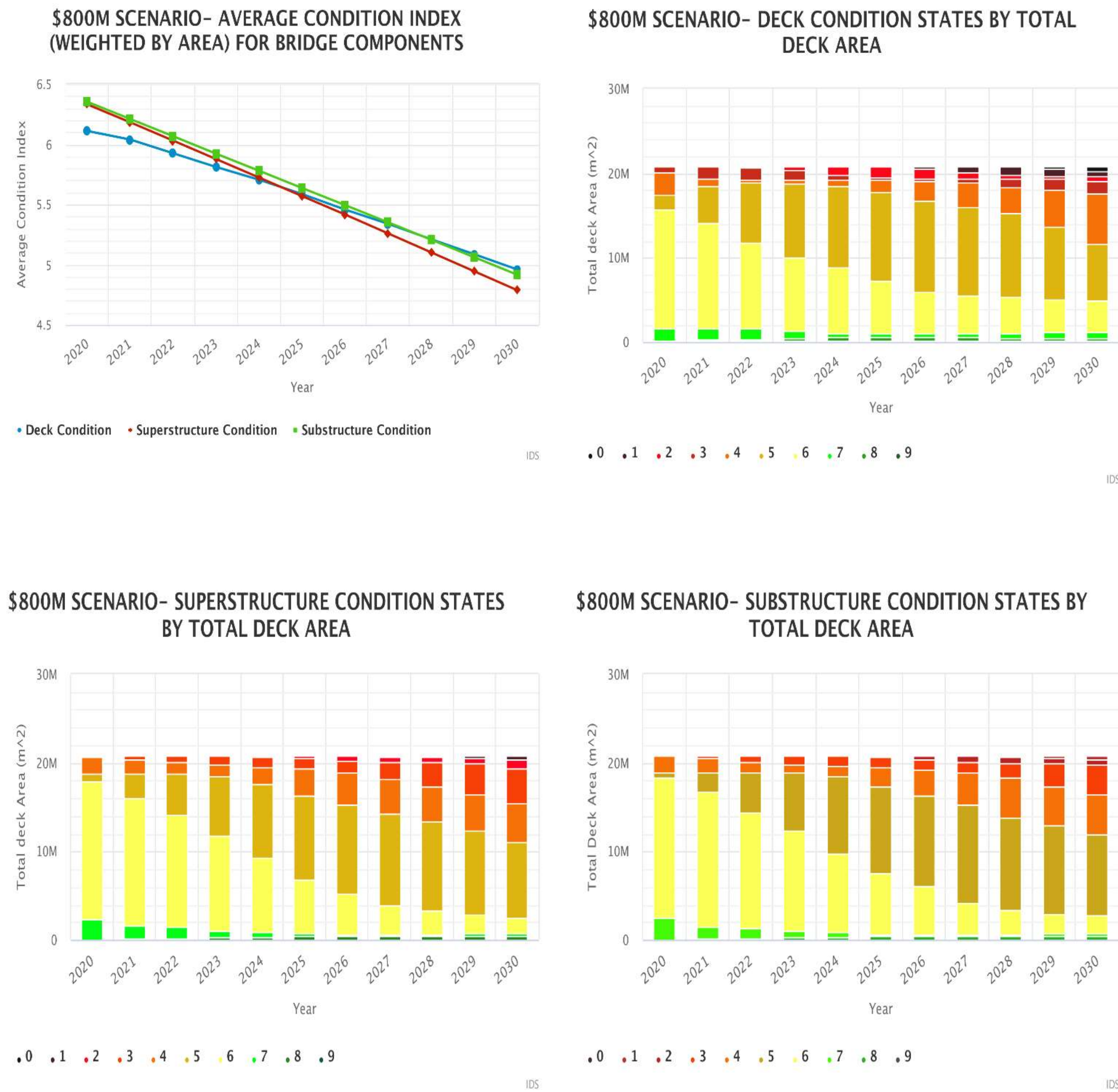


Figure 64. Example results of the $800 million scenario showing weighted-average condition index and condition states of deck, superstructure and substructure components by deck area.

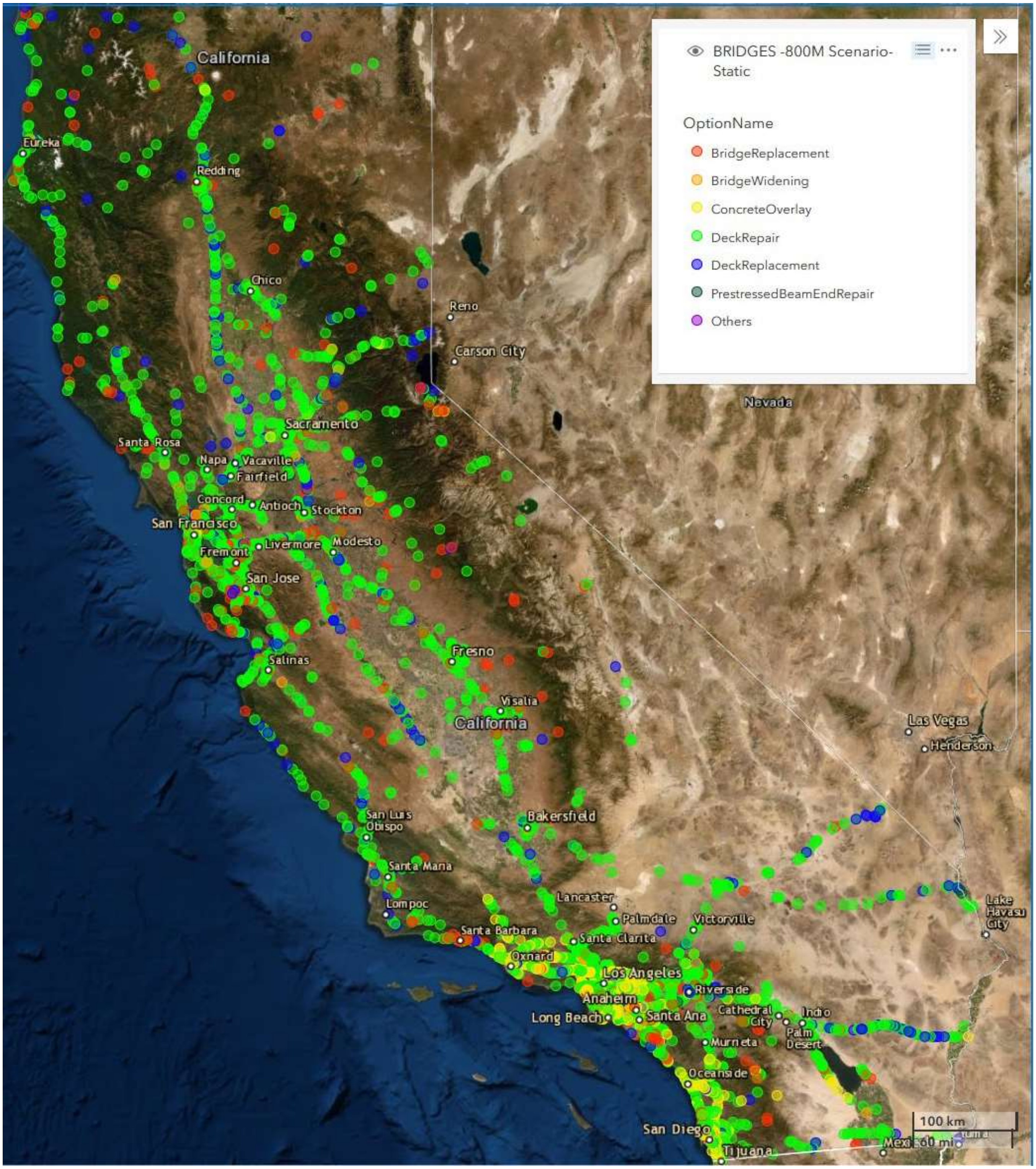


Figure 65. 10-year projects selected under the $800M scenario

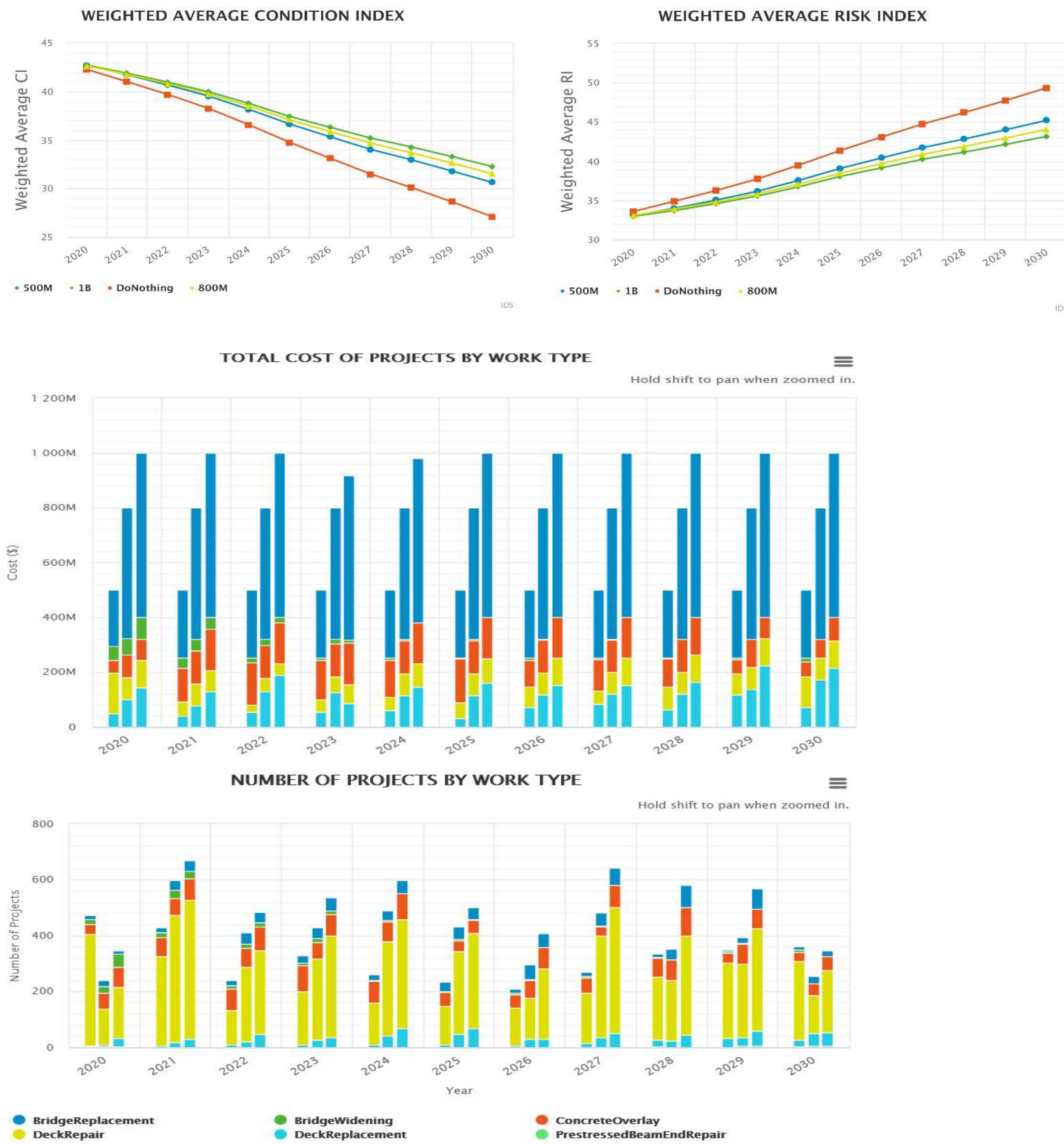


Figure 66. Comparison between four budget scenarios (Do-Nothing, $500M, $800M, and $1B), showing impact of different budget levels on system-level condition and risk indices.

Appendix B:

Preliminary Life Cycle Modeling and Planning Scenarios of Caltrans SHS Pavement

B.1 Data Sources and Analysis

Initially, we analyzed the publicly available Highway Performance Monitoring System (HPMS) data downloaded from the FHWA web site for 2016, 2017, and 2018 (https://www.fhwa.dot.gov/policyinformation/hpms/shapefiles.cfm). However, several data quality issues were found. For example, a large number of SHS pavement segments in 2016 data had the "Ownership" field incorrectly coded as '0' (instead of '1'). Condition data were mostly missing. Segments that had complete data were only about 4,000 centerline miles in total. HPMS data in 2017 and 2018 were also missing condition data for a large number of records. Caltrans subsequently provided an extract of HPMS 2018 data for the State Highway System (SHS) to be used for our analysis. This data set had fairly complete condition data (IRI, cracking, rutting, faulting). However, data on 'Year_Last_Improvement' (Item# 54) and 'Year_Last_Construction' (Item# 55) were missing. Therefore, for the purpose of our analysis, we made assumptions to estimate 'Year_Last_Improvement' value based on the condition state reported, assuming an average useful life for various surface types and functional classifications.

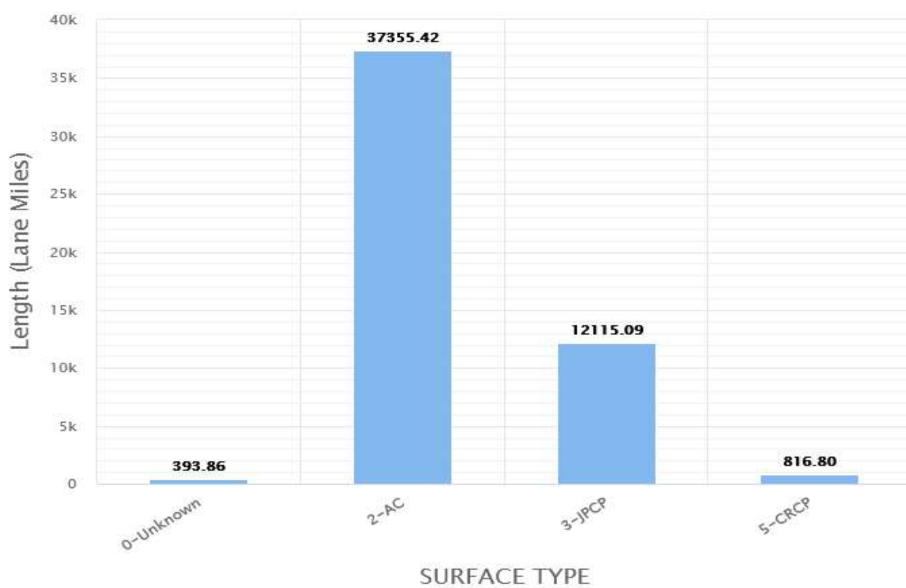


Figure 67: Length of SHS Pavement by Surface Type (2018)

Based on Caltrans 2018 HPMS data, the SHS pavement inventory includes 187,538 segments, with a total length of 50,681 lane miles (~14,820 centerline miles). Bridge decks and approach slabs, tunnels, and causeways are not included in this pavement inventory. The network includes approximately 37,355 lane miles (74%) of asphalt concrete (AC) pavement, 12,115 lane miles (24%) of Jointed Plain Concrete Pavement (JPCP), and 817 lane miles (2%) of Continuously Reinforced Concrete Pavement (CRCP) (Figure 67).

Figure 68 and Figure 69 show the breakdown of the total length of pavement segments based on highways functional classification, and surface type.

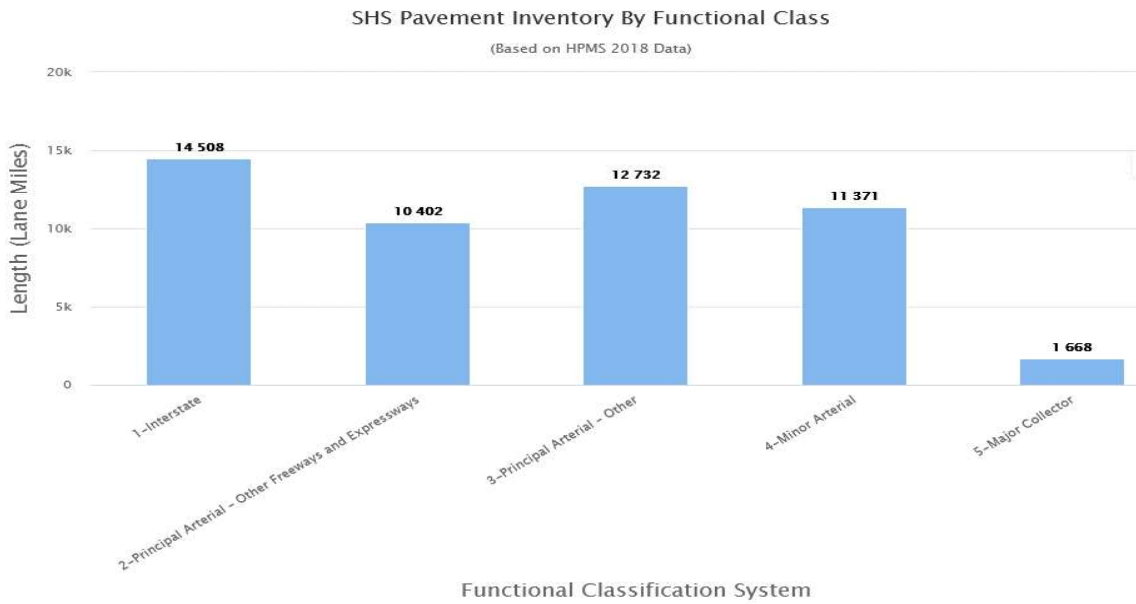


Figure 68: Length of SHS Pavement by Functional Classification

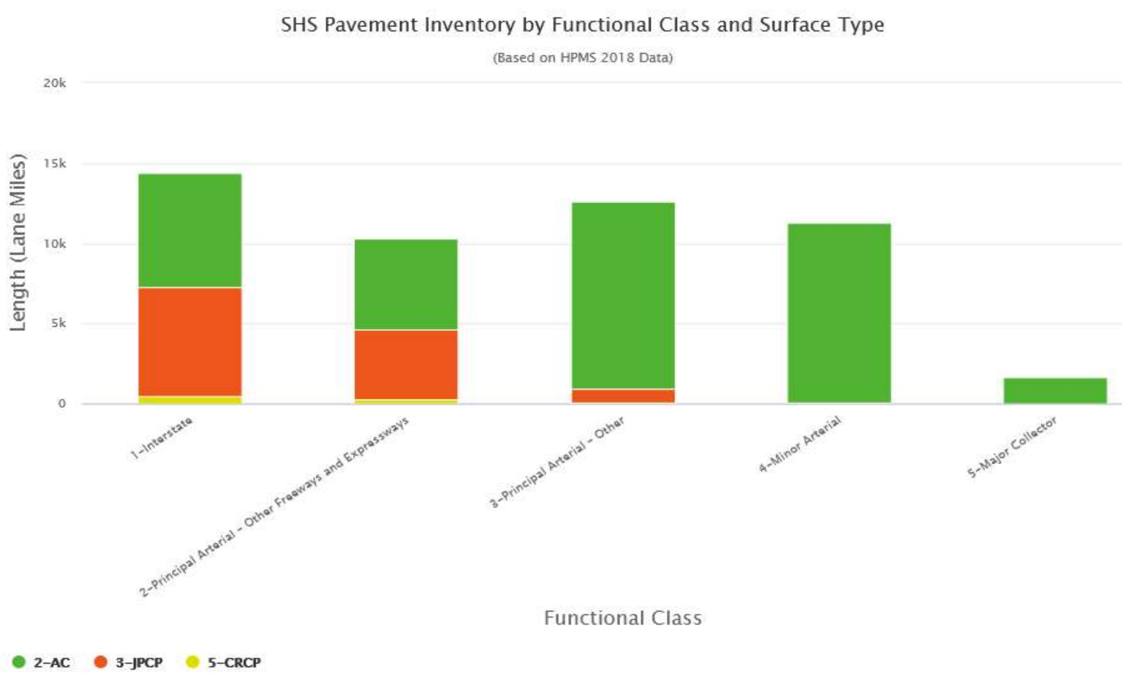


Figure 69: Length of SHS Pavement by Functional Classification and Surface Type

Figure 70 and Figure 71 show the total length and surface type of the pavement inventory for the National Highway System (NHS) and non-NHS.

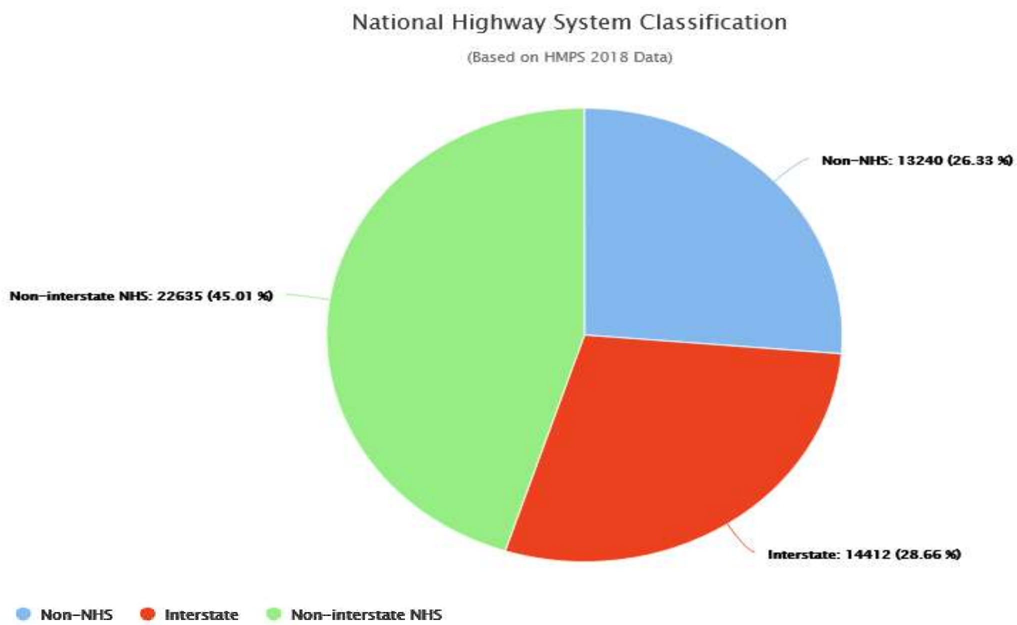


Figure 70: Length of SHS Pavement for NHS and non-NHS Highways

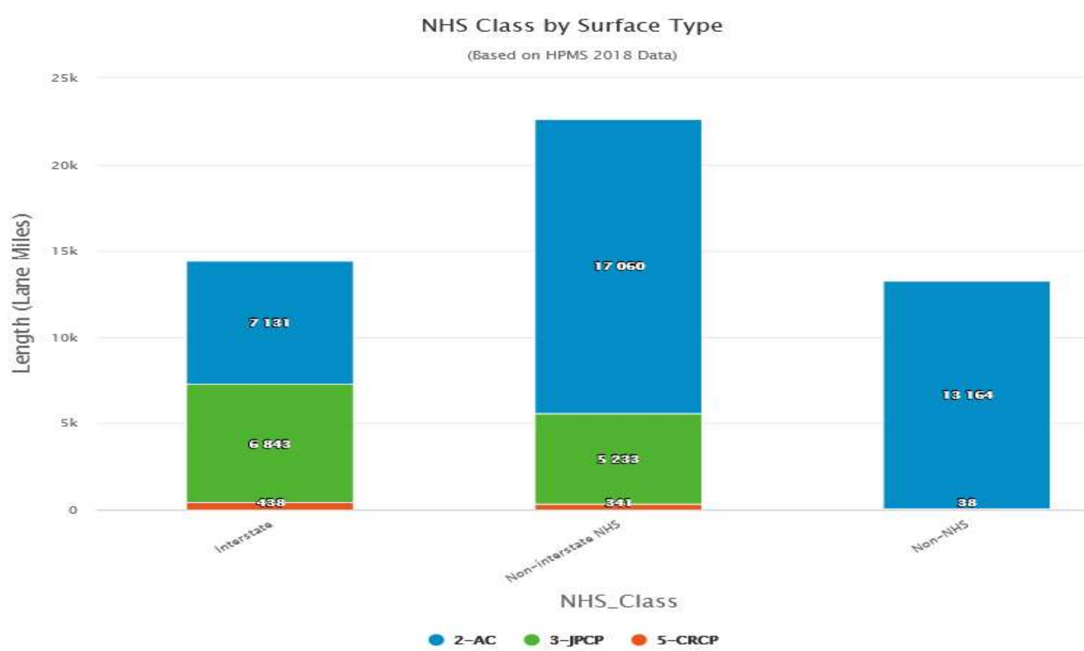


Figure 71: Length of SHS Pavement by Surface Type for NHS and non-NHS Highways

The SHS pavement inventory has an annual travel of approximately 180,119 million vehicle miles (MVMT). Approximately 95% of travel occurs on the NHS system (split almost in half between interstate and non-interstate), whereas travel on non-NHS system accounts only for 5% of the total travel (Figure 72).

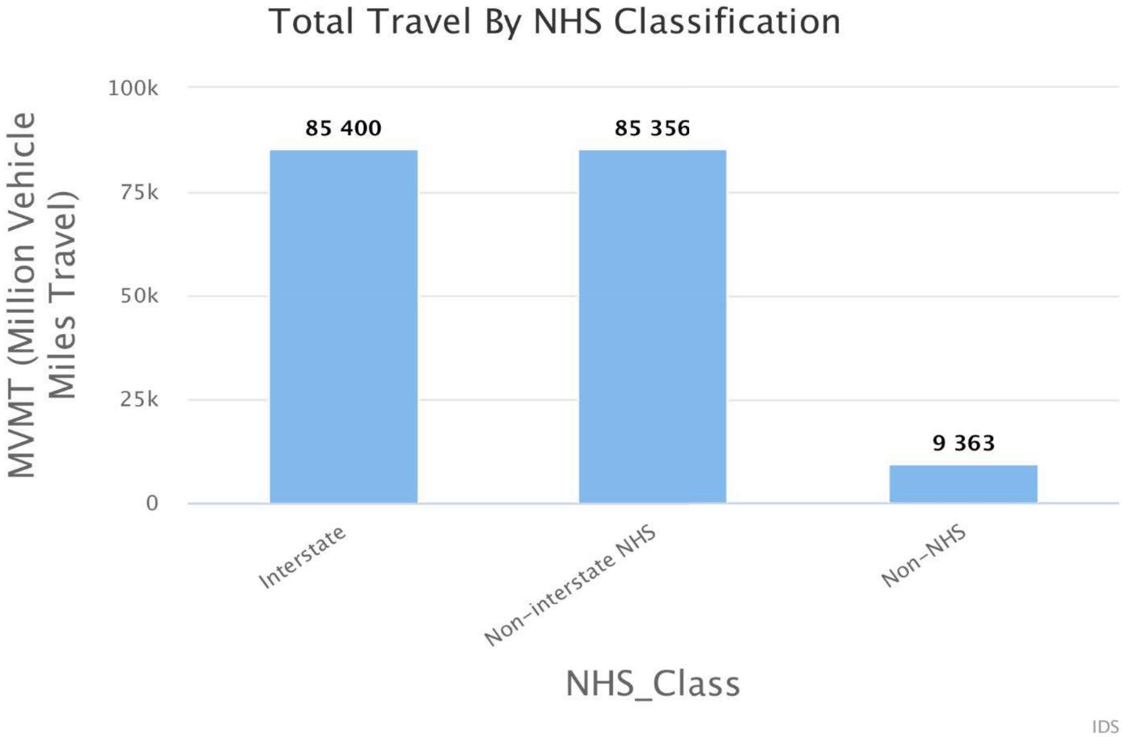


Figure 72: Length of SHS Pavement by NHS Classification

Initial modeling and planning were performed using HPMS fine segmentation data, which included approximately 198,583 segments. Although these fine segments are useful in capturing small performance changes across the network, planning scenario results using these fine segments produced a large number of small projects, mostly with impractical size. Generating practical projects based on these fine segments would require additional post-processing to spatially aggregate these small projects into larger meaningful projects with practical size. To overcome this limitation, the pavement coarse segments data (2016) has been later used for modeling. This data set included approximately 4,329 segments. However, the data set was missing pavement distress data that existed in the HPMS fine segments data. A spatial join of the coarse segments data and HPMS 2018 data (Figure 73) was performed to estimate average values of pavement distresses for the coarse segments, including average IRI, rutting, cracking, and faulting. Using coarse segmentation data, pavement performance models were developed for each SHS pavement class (I, II, and III) for HMA and JPC surface types.

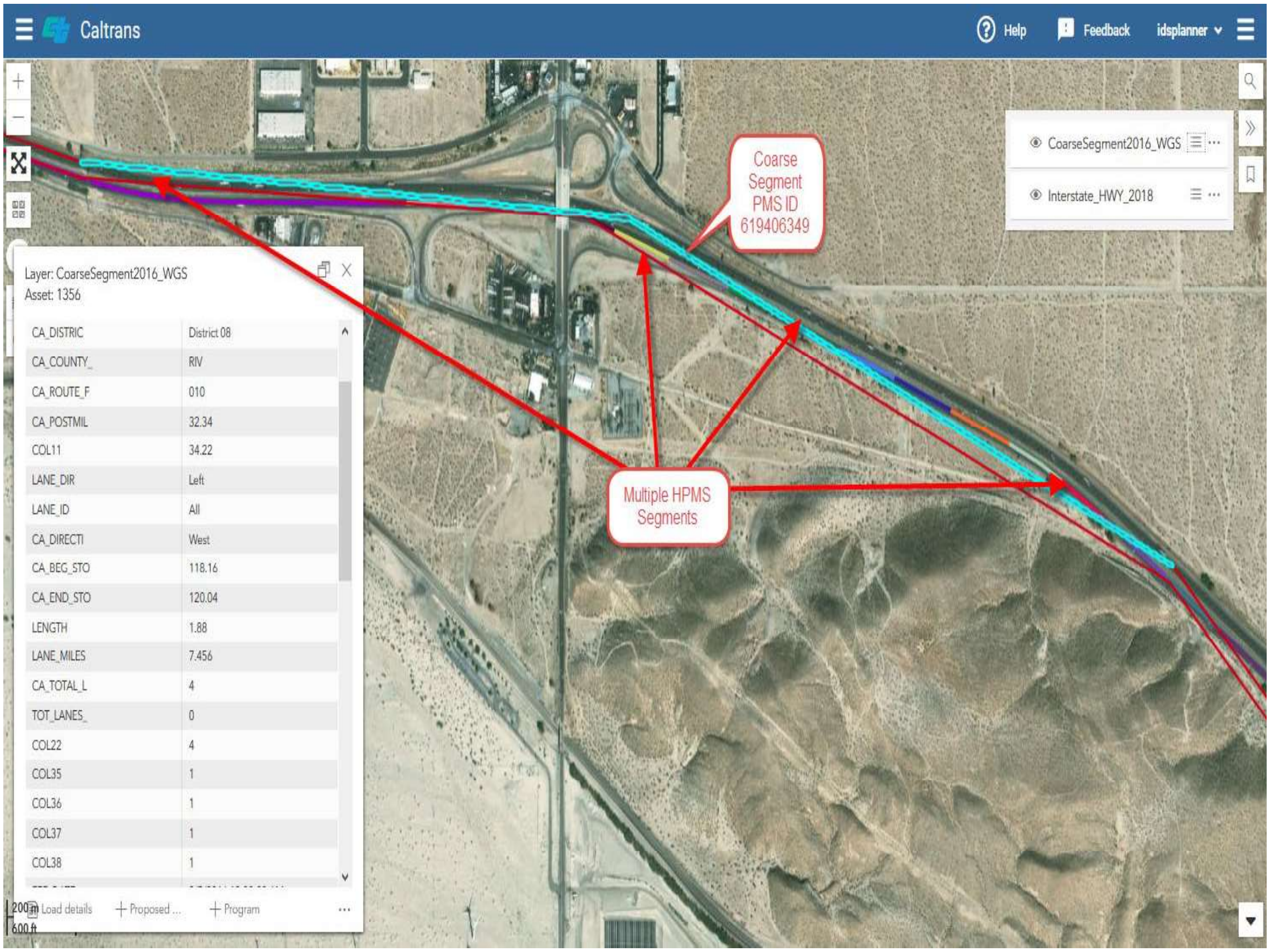


Figure 73: Spatial join of SHS Coarse Segments and HPMS Data to Calculate Average Distresses in Coarse Segments.

B.3 Pavement Condition Data and Performance Measures

Caltrans 2018 HPMS data included information on three (3) main distresses: cracking, international roughness index (IRI), and rutting (for AC pavement) and faulting (for JPCP and CRCP pavement). Pavement condition is assessed into categories of Good, Fair, and Poor based on the national FHWA final rule of the MAP-21 performance measures. The condition metrics include:

- Cracking Percentage.
- International Roughness Index (IRI).
- Rutting (for flexible pavement).
- Faulting (for rigid pavement).

For each of these metrics, FHWA has established thresholds as shown in Table 17.

Table 17. Performance thresholds for pavement condition categories

Condition Metric	Good	Fair	Poor
IRI (inches/mile)	<95	95-170	>170
Cracking (% area)			
AC	<5	5-20	>20
JPCP	<5	5-15	>15
CRCP	<5	5-10	>10
Rutting (inches)- For AC pavement	<0.2	0.2-0.4	>0.4
Faulting (inches)- For JPCP and CRCP	<0.10	0.10-0.15	>0.15

After calculating the condition metrics for each pavement segment, the overall condition state of the segment is calculated as shown in Table 18.

Table 18. Calculation of Pavement Overall Condition Measure

Overall Segment Condition Rating	AC or JPCP	CRCP	Measure
Good	All 3 metrics (IRI, Cracking, and Rutting/Faulting) rated as “Good”	IRI and Cracking are rated as “Good”	% of lane miles in “Good” condition
Poor	2 or 3 metrics rated as “Poor”	IRI and Cracking are rated as “Poor”	% of lane miles in “Poor” condition

Current performance measures for SHS pavement inventory (Figure 74) indicate that 21,488 lane miles (or 43%) are in good condition, 27,580 lane miles (55%) are in fair condition, and 1,260 lane miles (2.5%) in poor condition.

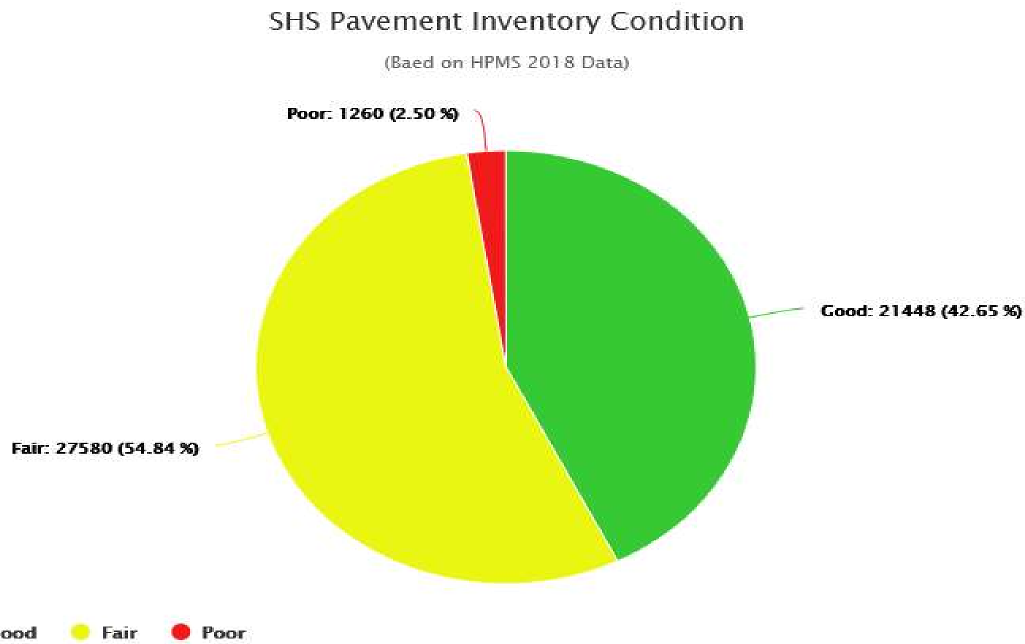


Figure 74: Current Performance Measures (2018) of the SHS Pavement Inventory

Distribution of the total travel (Figure 75) indicates that only about 2.5% of total travel is on pavement with poor condition, while 43% is on pavement with good condition.

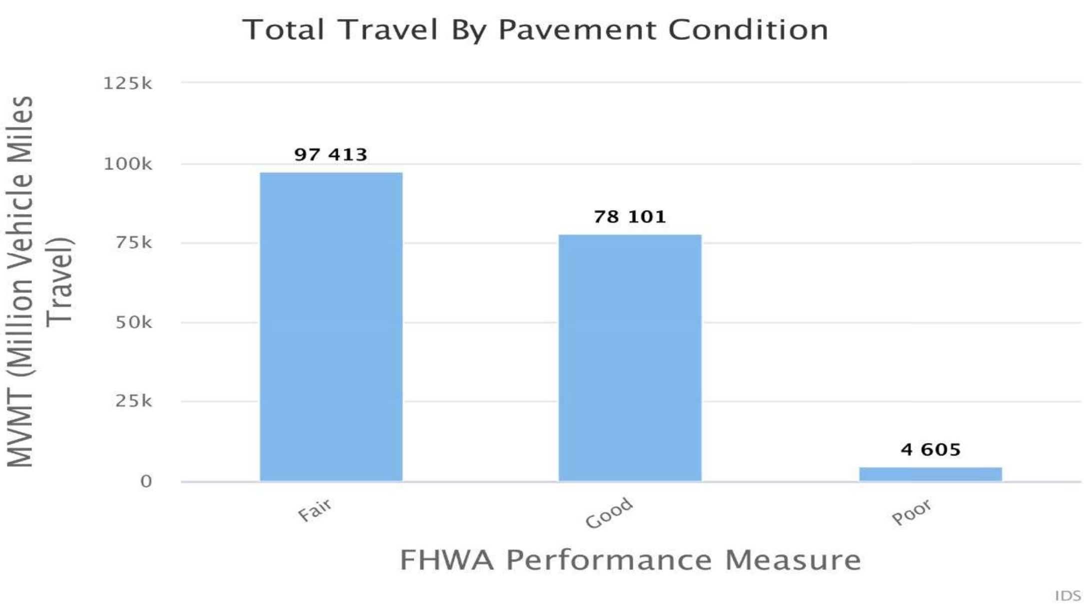


Figure 75: Total Annual Travel on Pavement in Different Condition States

Figure 76, Figure 77, and Figure 78 show pavement length in different condition states broken down by NHS class (NHS and non-NHS), functional class, and surface type, respectively.

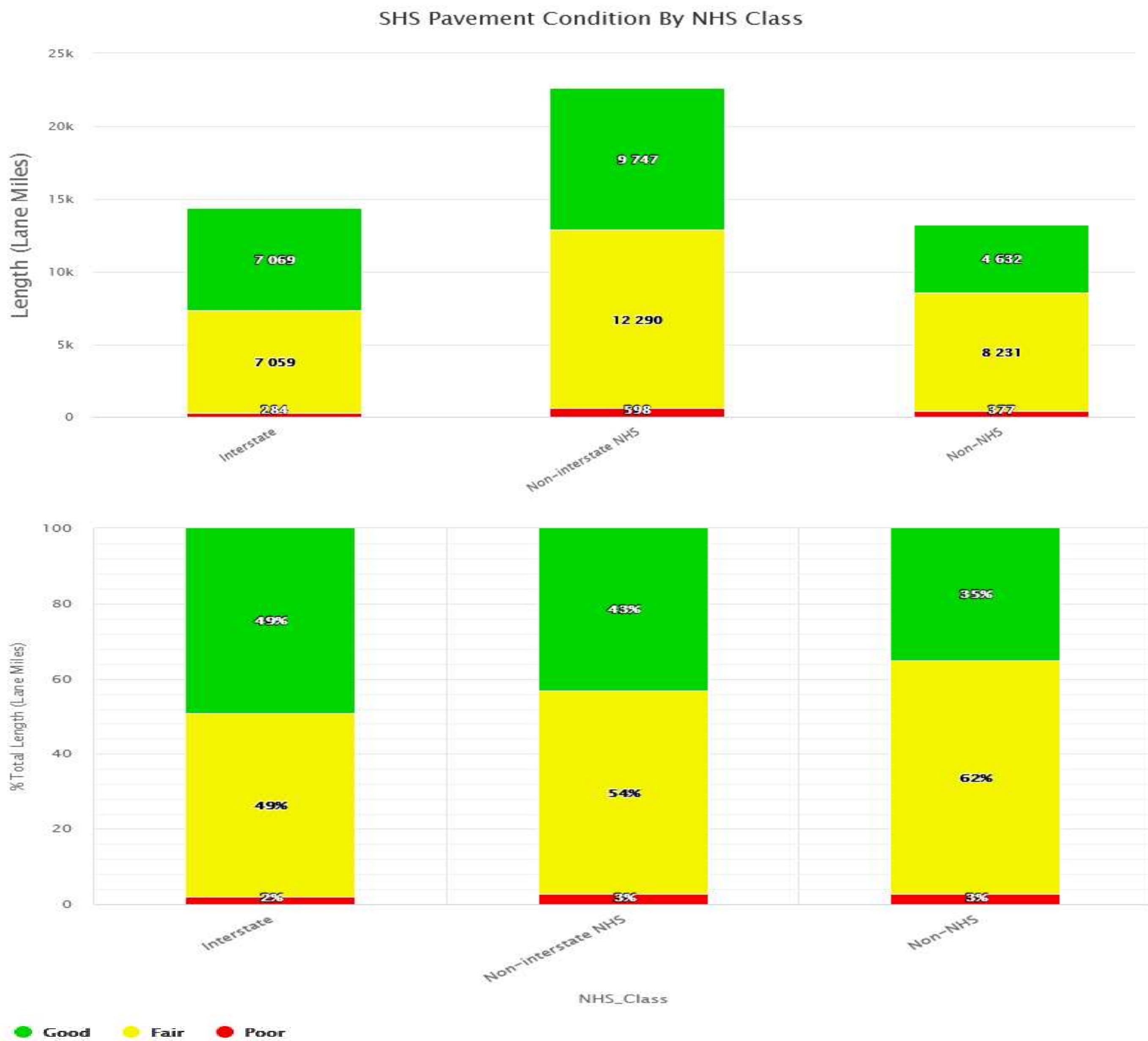


Figure 76: Total Length of Pavement in Different Condition States for NHS and non-NHS

The total lane miles and percentage of Good, Fair, and Poor pavement from our analysis are close to the numbers reported in Caltrans 2018 Pavement Report Card for the interstate system. However, the numbers for the non-interstate NHS in the Report Card included both the SHS non-interstate NHS (22,490 lane miles) as well as local (off SHS) NHS segments (approximately 19,426 lane miles), and therefore they were different from the numbers shown in Figure 76.

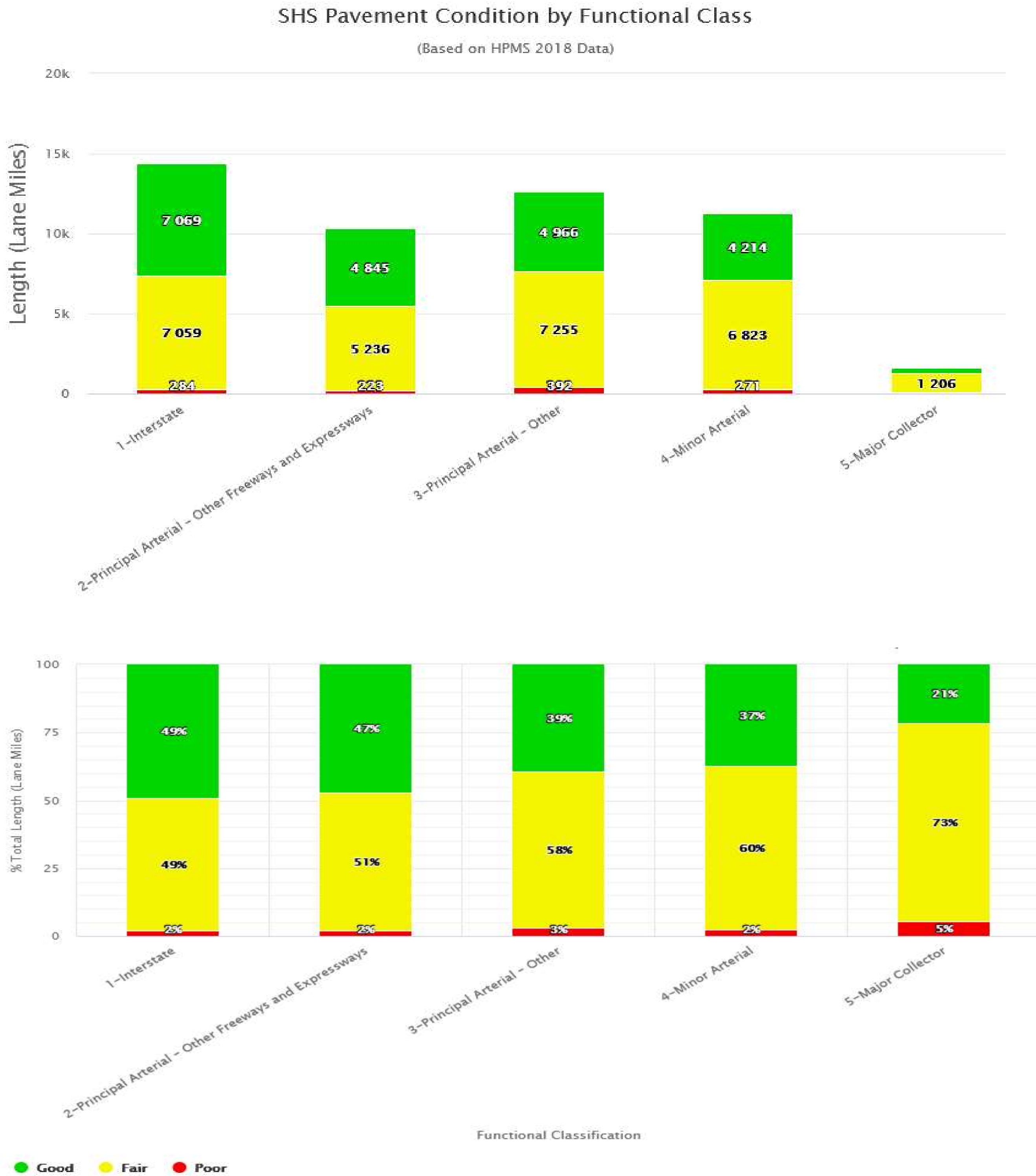


Figure 77: Total Length of Pavement Assets in Different Condition by Functional Class

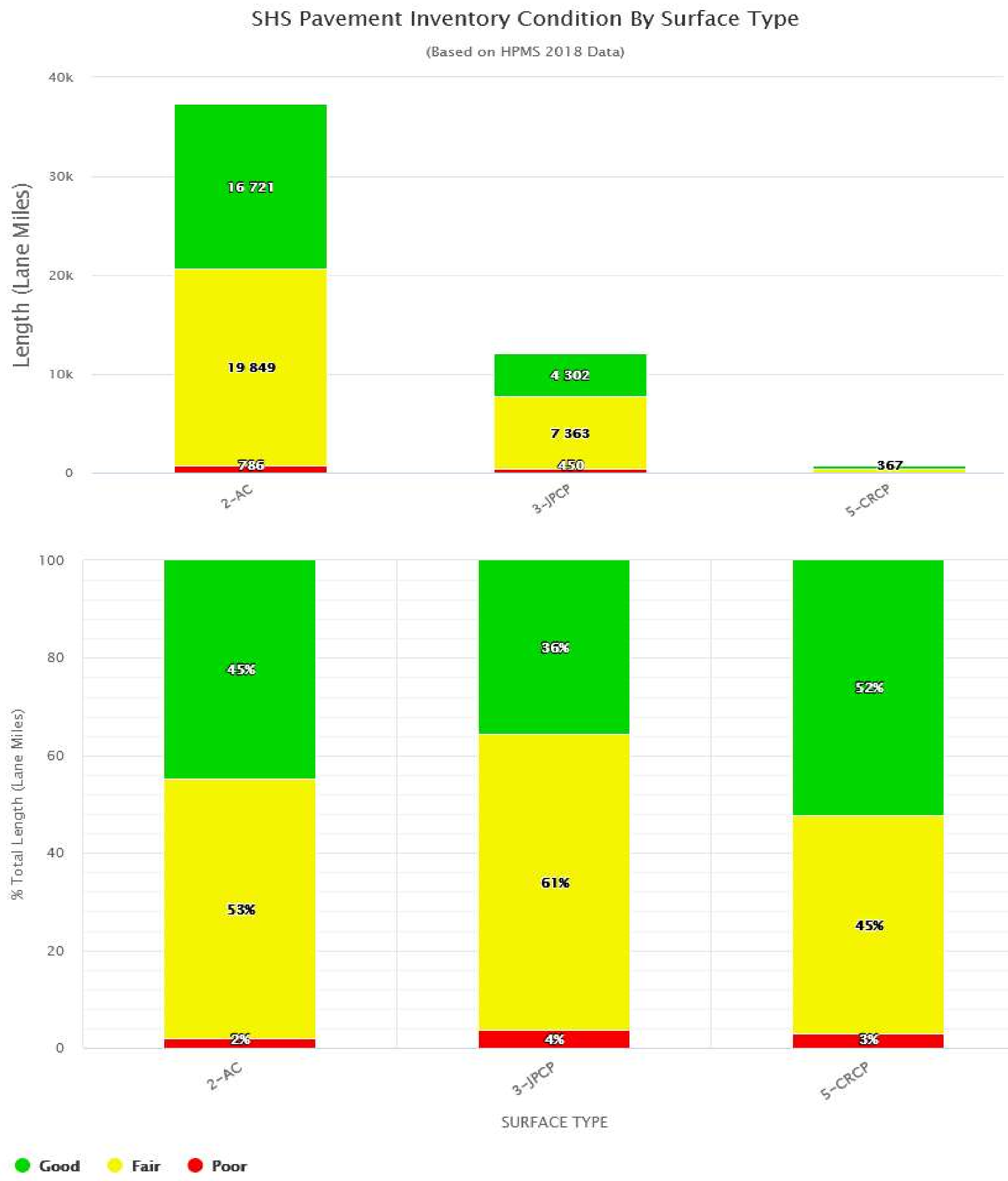


Figure 78: Total Length of Pavement Assets in Different Condition by Surface Type

B.4 Development of Pavement Condition Indices

Individual indices were developed to measure and evaluate the four main surface distresses: cracking, roughness, rutting (for flexible pavement), and faulting (for rigid pavement). An overall Pavement Condition Index (PCI) is then calculated based on the individual distress indices. The methodology to calculate distress and condition indices follows the approach developed by the Institute for Transportation and used in Iowa DOT[2]. To differentiate the calculated PCI from the ASTM standard measure, this PCI will be referred to as PCI Version 2 (or PCI_2). For simplicity, the indices are defined using a 100-point scale, where 100 indicates “as new” condition (or no distress) and 0 indicates “worst condition” (i.e., distresses exceed a defined failure threshold).

Roughness index is calculated based on IRI, whereas IRI values <= 30 inch/mile are considered as a perfect index (100) and values >=250 are considered very poor (0 index). FHWA recommends that an IRI < 95 inch/mile is considered smooth (i.e., good) and an IRI > 170 inch/mile is considered rough (i.e., poor). Equation 1 shows the formula for calculating the Roughness Index for IRI values between 30 and 250.

Roughness Index = (250-IRI) * 100/220 Equation 1

Calculation of the Rutting Index was based on the reported rut depths available in HPMS data. According to the NCHRP Synthesis report, a threshold of 12 millimeter (approximately 0.5 inch) was found represent a safety concern (i.e., 0 index). Equation 2 shows the formula for calculating the Rutting Index for ruth depth values < 0.5 inch.

Rutting Index = (0.5-Rutting Depth) * 100/0.5 Equation 2

Faulting Index for rigid pavement is calculated based on the reported faulting, whereas faulting values <=0.05 inches are considered as a perfect index (100) and values >=0.15 inches are considered very poor (0 index). Equation 3 shows the formula for calculating the Faulting Index for values between 0.05 and 0.15 inches.

Faulting Index = (0.15- Faulting) / (100/0.1) Equation 3

The original calculation of cracking index is based on combining and weighting of cracking indices for each type of cracking (longitudinal, transverse, fatigue, and wheel-path cracking). However, since the HPMS data does not include detailed information on cracking types, the overall percentage of total cracked area was used. Cracking index is calculated by scaling the percentage cracking reported in the HPMS data, while considering cracking percentage >= 30 to indicate a very poor or failed segment (i.e., 0 cracking index). Equation 4 shows the formula for calculating cracking index.

Cracking Index = (30-Cracking Percentage) * 100/30 Equation 4

[2] Bektas F, O. Smadi, and I. Nenanya. 2015. Pavement Condition: A New Approach for the Iowa DOT. Transportation Research Record: Journal of the Transportation Research Board, No. 2523, pp. 40–46.

A pavement segment overall condition index (PCI_2) is calculated by combining individual indices by weighting factors. Equations 5 and 6 below show the calculation of the PCI_2 condition index for flexible and rigid pavement segments, respectively.

PCI_2_{AC} = 0.4* Roughness Index +0.4* Cracking Index + 0.2* Rutting Index
Equation 5

$PCI\_2_{JPCP\ and\ CRCP}$ = 0.4* Roughness Index +0.4* Cracking Index + 0.2* Faulting Index
Equation 6

Figure 79 shows the distribution of the calculated SHS pavement condition index against the FHWA condition measures. The pavement segments in good condition showed a median condition index (PCI_2) of 90, whereas segments in fair condition have a median PCI_2 of 70, and those in poor condition have a median of 23. The interquartile range (IQR) of the pavement segments showed that 50% of segments in good condition have PCI_2 between 87 and 97, whereas the range for fair condition segments was between 56 and 79, and for poor condition segments was between 17 and 29.

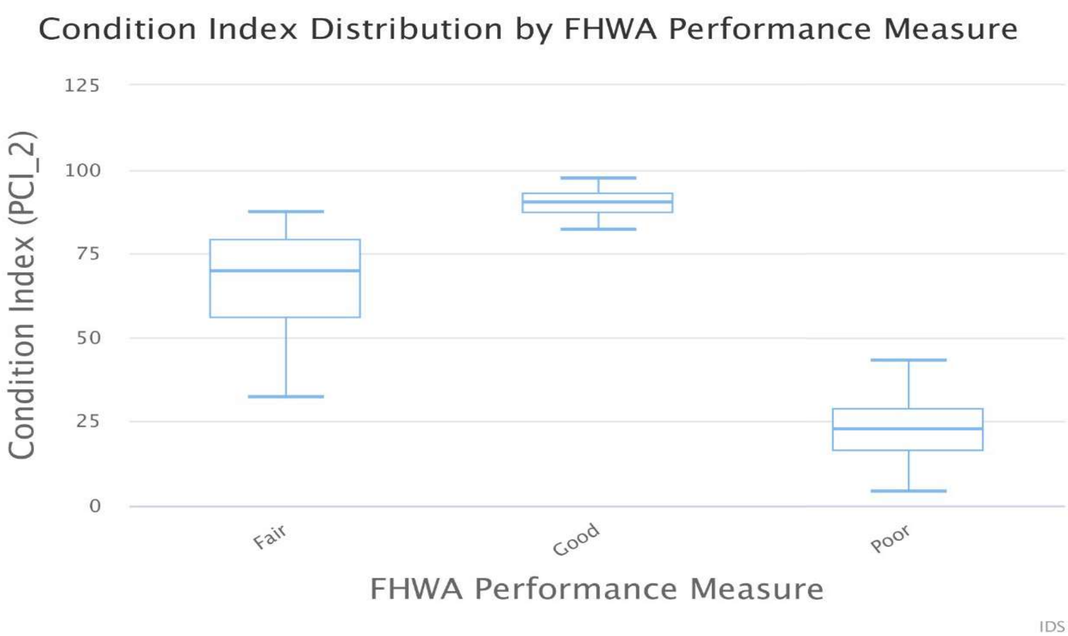


Figure 79: Correlation of Calculated PCI_2 and FHWA Performance Measures

Figure 80 shows the distribution of pavement condition index for NHS and non-NHS highways. Interstate, non-interstate NHS, and non-NHS pavement segments have an average PCI_2 of 85, 80, and 77, respectively.

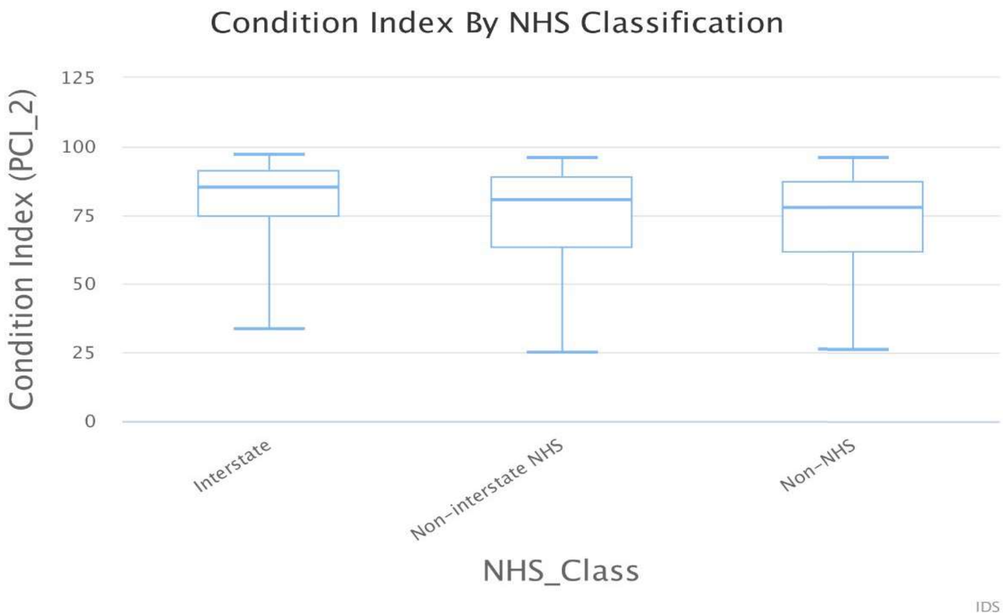


Figure 80: Condition Index (PCI_2) Distribution for NHS and non-NHS Highways

B.5 Defining Pavement Groups

Pavement assets were categorized into a set of groups based on their deterioration and risk characteristics. Groups are assumed to have somewhat homogeneous characteristics in terms of their deterioration rate and/or criticality (or expected consequence of failure). It is important to define groups at an appropriate level of granularity to balance the level of desired accuracy in predicting deterioration and criticality, with the time and effort needed to build group-specific deterioration and risk models.

Analysis of the SHS pavement data showed that pavement distresses and deterioration rates are primarily influenced by surface type, traffic volume, and functional classification. Initially, separate groups were defined for different surface types in the interstate and non-interstate systems. However, the AC non-interstate group was further divided into three sub-groups based on the traffic volume, AADT: Low, Medium, and High. The definition of the AADT thresholds were aligned with the criteria used by Caltrans[3], where the daily average ESAL levels to describe each of the three categories: Low (ESAL <60,000); Medium (60,000<=ESAL<300,000); High (ESAL >=300,000). Since the ESAL data was not available in HPMS, equivalent AADT was used to define our groups. Making some assumptions for converting ESAL to AADT, AADT thresholds of 4000 and 20,000 were used. Table 19 shows the definition of the 6 pavement groups

[3] Wang, Z.and Pyle, T., Implementing a pavement management system: The Caltrans experience, International Journal of Transportation Science and Technology, https://doi.org/10.1016/j.ijtst.2019.02.002

used in our analysis. Figure 81 shows the total number and percentage of each group, in total representing approximately 94% of the SHS pavement inventory.

Table 19. Definition of SHS Pavement Groups

Group ID	**Pavement Characteristics**	**Number of Segments**	**Total Length (Lane Miles)**
AC Interstate	AC; Interstate	17,013	7,131
AC Non-Interstate High Traffic	AC; Interstate; AADT >20,000	28,432	8,961
AC Non-Interstate Medium Traffic	AC; Interstate; 4,000 <AADT <= 20,000	52,882	10,234
AC Non-Interstate Low Traffic	JPCP and CRCP; Interstate); AADT <=4,000	60,109	11,029
JPCP_CRCP Interstate	JPCP and CRCP; Interstate	13,879	7,281
JPCP_CRCP Non-Interstate	JPCP and CRCP; Interstate	14,262	5,651
TOTAL		**186,577**	**50,287**

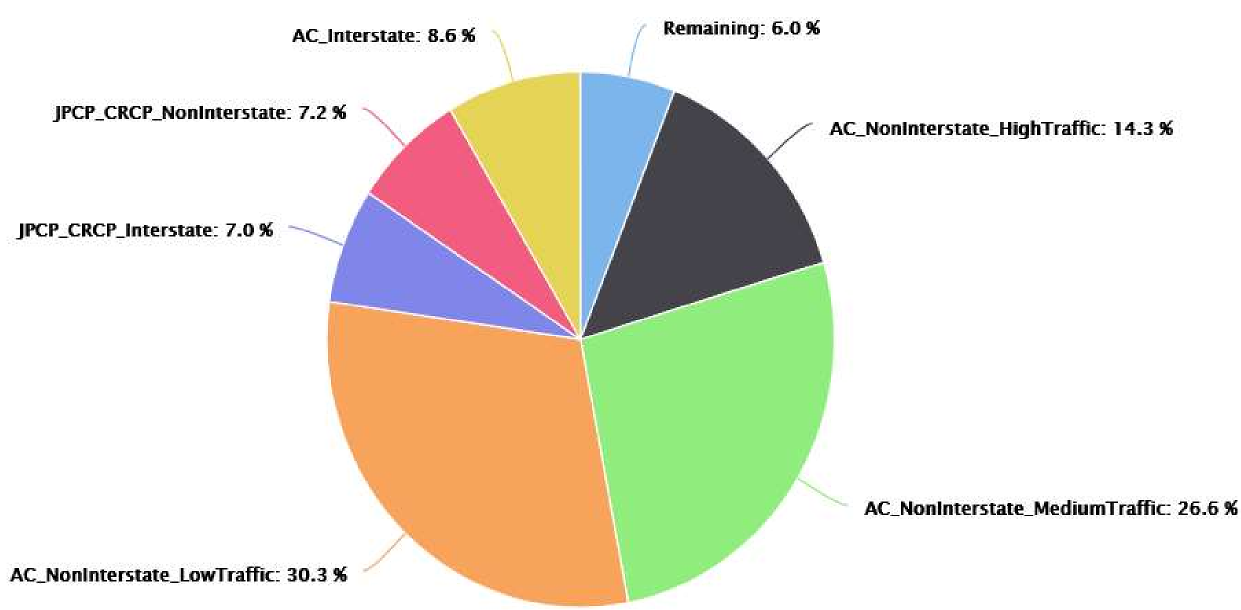


Figure 81: Number of segments in the defined groups as % of SHS pavement inventory

B.6 Defining Deterioration models for Pavement Groups

For each of the 6 defined group, models to predict the condition indices of each pavement segment were defined. As described above, calculating the condition index of a pavement segment (PCI_2) is derived from the segment's indices for the main distresses: cracking, roughness, rutting, and faulting indices. Therefore, models were required to predict progression of the defined distresses in each group.

Models to predict IRI, Cracking, and Rutting were defined for each of the four AC pavement groups, whereas models to predict IRI, Cracking, and Faulting were defined for the two concrete pavement groups. In total, 18 models were defined (three per group) to predict distress progression for each group.

Figure 82 shows an example of examining different distributions to define deterioration model parameters for cracking, IRI, and rutting in the AC-Interstate group.

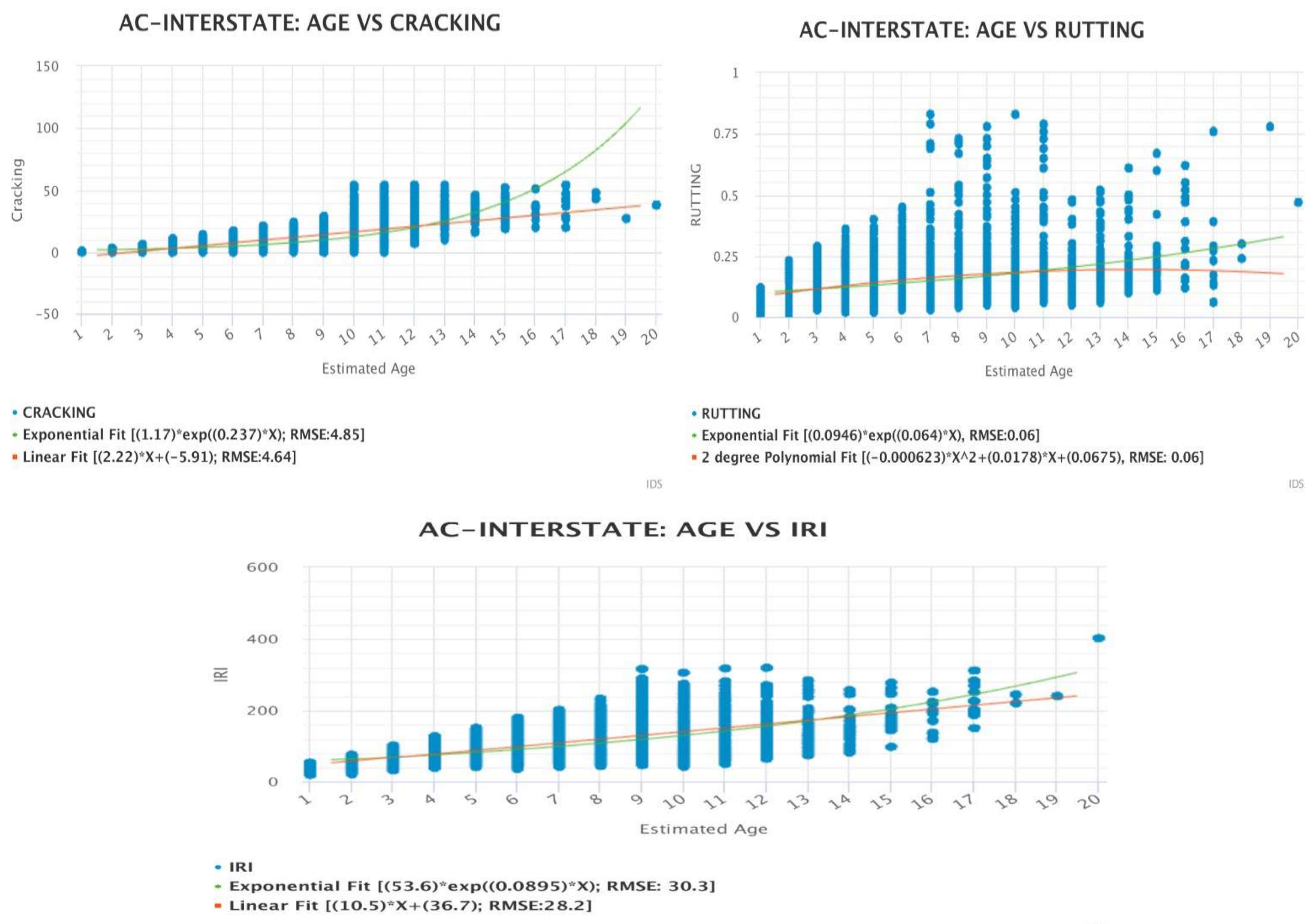


Figure 82: Examining different distributions to model deterioration of AC Interstate pavement.

Examining the distribution of condition indices with estimated age of pavement segments, and investigating a number of polynomial, exponential, linear, and Weibull functional forms, we found that an exponential distribution seems to correlate well with data and provides reasonable predictions, and therefore were used it to model the progression of each distress. The function for an exponential distribution is given by Equation 7.

$$f(x) = a\, e^{b\,X} \qquad \text{Equation 7}$$

The first parameter, a, represents the value at the base year (i.e., first year data is available), and the second parameter, b, represents the average annual progression (or growth) rate. The best fit of the exponential parameters was determined based on examining data distributions and observing the value of the root-mean-square error (RMSE) for each combination of the parameters. Based on this analysis, the exponential distribution parameters are determined for each distress type in each group (Table 20).

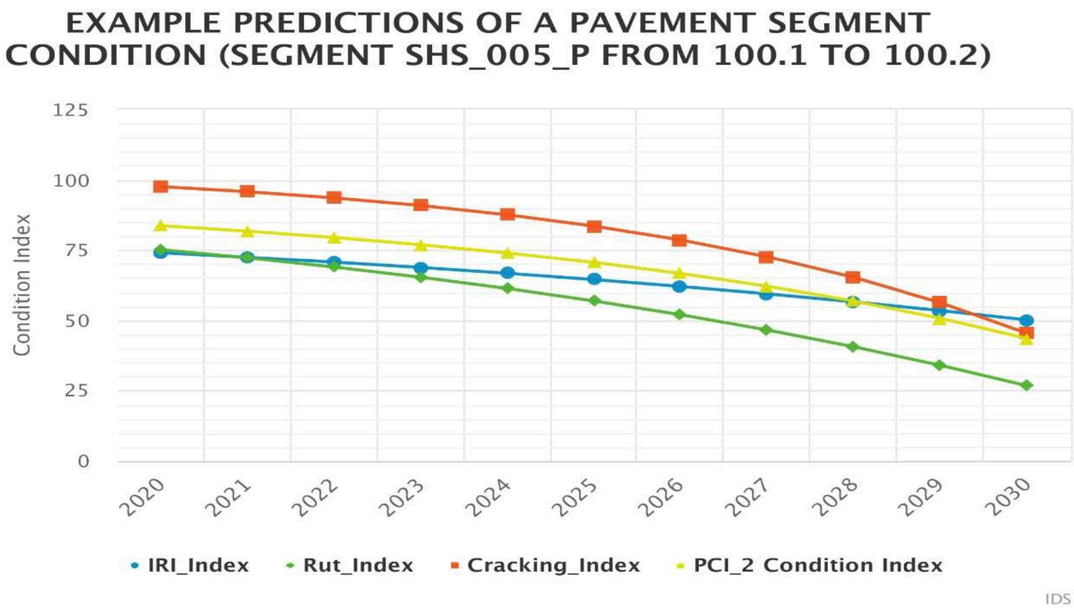
Table 20. Exponential Parameters (a, b) for Modeling Pavement Distress Progression

Group ID	Cracking		Roughness		Rutting		Faulting	
	a	b	a	b	a	b	a	b
AC Interstate	1.17	0.2	30	0.08	0.09	0.1		
AC Non-Interstate High Traffic	1.59	0.189	40	0.06	0.07	0.065		
AC Non-Interstate Medium Traffic	2.12	0.179	30	0.077	0.07	0.076		
AC Non-Interstate Low Traffic	1.72	0.189	30	0.079	0.06	0.08		
JPCP_CRCP Interstate	4.86	0.05	40	0.04			0.04	0.03
JPCP_CRCP Non-Interstate	7.06	0.02	40	0.04			0.04	0.03

Each of the defined models represents the average deterioration of a group of pavement segments. However, in reality, individual pavement segments within a particular group are rarely identical and often deteriorate at different rates. Therefore, predicting the condition indices of a particular pavement segment should always take into consideration the initial values of the distresses. In essence, the defined models should be used to predict the distress progression starting from initial values, as recorded in the HPMS 2018 data. Starting from an initial state, the models can then be used in an incremental recursive manner to predict future values, where the value in a specific year would be calculated based on the initial value known at a previous year. The incremental modeling approach was described in detail in the previous progress report.

Figure 83 shows an example for predicting various condition indices of AC Interstate segment. It also shows predictions of future IRI values for sample pavement segments in different groups.

Once the distresses are predicted for each pavement segment using the defined exponential models, condition indices (IRI_Index, Rutting_Index, Faulting_Index, and Cracking_Index) can then be calculated using Equations 1, 2, 3, and 4, respectively. The overall condition index (PCI_2) can then be calculated using Equations 5 and 6, depending on the pavement surface type.



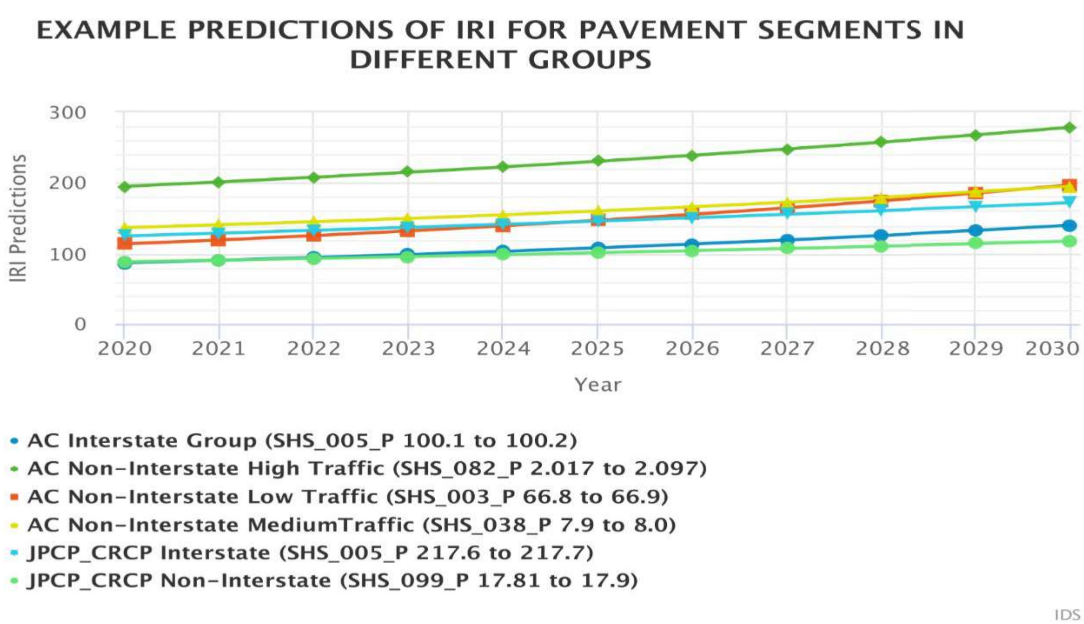


Figure 83: Example for predicting condition indices of AC Interstate segment (top) and predictions of IRI for pavement segments in different groups (bottom).

B.7 Risk Model and Criticality Factors

We employed a risk-based approach for lifecycle planning (LCP) of the pavement inventory. Unlike traditional condition-based LCP approach, a risk-based approach has the advantage of combining the pavement condition (or likelihood of failure) and criticality (or consequence of failure) to prioritize and select projects based on system-level risk measures. Criticality of pavement sections is typically reflected in the functional classification and traffic volumes.

Under traditional condition-based approaches for selecting projects, pavement assets are typically separated into different asset classes based on their criticality or functional classification. For example, plans may be developed separately for interstate and non-interstate systems, or other functional classification. Funding is also allocated to these different systems based on their relative criticality levels. However, using a risk-based approach, considerations for asset criticality can be made more explicit, allowing us to quantify the impact of investment decisions and project selection on the entire asset inventory and to find the best trade-offs to balance the needs by minimizing overall system-level risk.

A simple criticality model that considers three main factors was used. The factors include: (1) functional classification; (2) total traffic volume; and (3) whether the pavement segment is NHS. For each criticality factor, a “weight” is assigned to reflect its relative importance. The weights assumed for the three factors were: 0.5, 0.2, and 0.3, respectively. A pavement segment “criticality index” was then calculated as a weighted average of the values of the criticality factors, as shown in Equation 8.

$$Criticality\_Index_i = \sum_{j=1}^{N} W_j \, CF_j \qquad \text{Equation 8}$$

Where,

$Criticality\_Index_i$ = Pavement segment i Criticality Index

CF_j = Value of Criticality Factor j for pavement segment i

W_j = Agency-defined weight for Criticality Factor j

N = Number of criticality factors considered

An overall “risk index” for each pavement segment is subsequently calculated based on its condition index (PCI_2) and Criticality Index (Equation 9).

RI = (100- PCI_2) * Criticality Index Equation 9

Figure 84 shows a summary of the main components of the proposed pavement risk model.

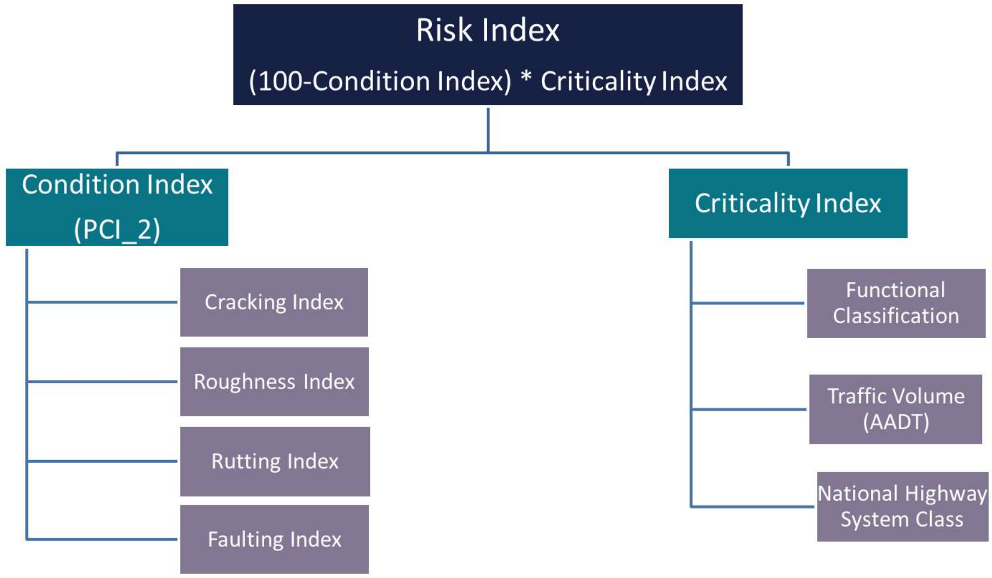


Figure 84: Proposed Pavement Risk Model

B.8 Pavement Treatments Models

To achieve the best cost-benefit trade-off, the optimization process evaluates candidate treatments in each year in the planning horizon based on defined applicability constraints, as well as cost and benefit models. In defining treatments models and constraints, several Caltrans documents were used[4].

A range of treatments for flexible and rigid pavement have been defined including various preservation, rehabilitation, or replacement actions were considered. A simplified version of Caltrans decision trees was implemented to align with rules and constraints governing the applicability of each treatment. The current treatments include six defined for flexible pavement and five defined for rigid pavement. Treatments for flexible pavement include: thin HMA overlay, medium HMA overlay, thick HMA overlay, seal coat, cold-in-place recycling, and full depth reclamation. Treatments for rigid pavement include: diamond grinding, grinding and slab replacement, slab replacement, concrete overlay, and PCC lane replacement. The list of treatments can be easily extended to include other treatments used at Caltrans.

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[4] Maintenance Technical Advisory Guide Volume I- Flexible Pavement Preservation (2nd Edition), 2008

Volume II - Rigid Pavement Preservation 2nd Edition, Framework for treatment Selection, 2007

Wang, Z. and Pyle, T., Implementing a pavement management system: The Caltrans experience, International Journal of Transportation Science and Technology, https://doi.org/10.1016/j.ijtst.2019.02.002

Cost and effectiveness models for each treatment were used to estimate expected total cost and impact when the treatment is applied on a specific pavement segment. Approximate unit costs for these treatments were estimated using published Caltrans documents. Expected improvements for each of these treatments were estimated based on our assumptions and judgment. For a more rigorous pavement planning effort, these assumptions and models will need to be reviewed and refined with Caltrans staff to ensure consistency with current work practices and local experience. Table 21 summarizes the rules used to define the applicability constraints of different treatments.

Table 21. Treatments' applicability criteria

Treatment	Surface Type	Cracking Area%	IRI (in/mile)	Faulting (in.)	AADT	Through Lanes	Condition Index (PCI_2)
Thin HMA Overlay	AC	5%-20%	<=170		<=60,000	Any	40-70
Medium HMA Overlay	AC	5%-30%	95-500		<=100,000	Any	30-60
Thick HMA Overlay	AC	30%-100%				Any	10-50
Seal Coat	AC	5%-15%	<=200		<=15,000	Any	40-70
Cold-in-Place Recycling (CIR)	AC	20%-60%	Any		>=500	Any	0-60
Full Depth Reclamation	AC	>=30%	Any		>=375	Any	0-40
Grinding	JPCP	1%-5%	95-300	0.1 - 1.0	Any	Any	40-70
Grinding and Slab replacement	JPCP	1%-10%	90-500	0.1 - 1.0	Any	Any	30-70
Slab Replacement	JPCP	1%-10%	95-500	0.1 - 1.0	Any		40-70
Concrete Overlay	JPCP, CRCP	10%-100%	Any		Any	<=6	0-60
PCC Lane Replacement	JPCP, CRCP	>=20%	Any	>=0.1	Any	>=7	0-40

Treatments' effectiveness are defined in terms of incremental improvements to different distresses. Examples of improvements include lower roughness, cracking, or rutting in a pavement segment. Table 22 summarizes the unit costs and condition improvement for each of the defined treatments.

Table 22. Assumed unit costs and condition improvements

Treatment	Unit Cost (Per Lane Mile)	Expected Improvements (Effectiveness)
Thin HMA Overlay	$152,000	Reduce IRI by 250 in/mile, and rutting by 1 inch, and cracking area by 30%.
Medium HMA Overlay	$325,000	Reduce IRI by 500 in/mile, and rutting by 1 inch, and eliminates all existing cracking.
Thick HMA Overlay	$720,000	Eliminates roughness, rutting, and cracking.
Seal Coat	$57,000	Reduce IRI by 250 in/mile, and rutting by 1 inch, and eliminates cracking.
Cold-in-Place Recycling (CIR)	$350,000	Eliminates roughness, rutting, and cracking.
Full Depth Reclamation	$1,002,000	Eliminates roughness, rutting, and cracking.
Grinding	$130,000	Reduces faulting by 1 in, and cracking by 5%.
Grinding and Slab replacement	$330,000	Reduce roughness by 500 in/mile, cracking area by 50%, and faulting by 1 in.
Slab Replacement	$100,000	Eliminates roughness, cracking, and faulting.
Concrete Overlay	$475,000	Eliminates roughness, cracking, and faulting.
PCC Lane Replacement	$2,600,000	Eliminates roughness, cracking, and faulting.

B.9 System-Level Condition and Risk Metrics

The optimization objective function used for project selection is formulated to maximize system-level condition or minimize system-level risk index at the lowest lifecycle cost. These two system-level measures are calculated using a weighted average value based on total length of pavement segments (in lane miles) to represent the overall system condition and risk levels. System-level weighted average condition index (WACI) and risk index (WARI) are calculated as shown in Equations 10 and 11, respectively.

$$WACI = \frac{\sum_{i=0}^{N} PCI_i \ Length_i}{\sum_{i=0}^{N} Length_i}$$ Equation 10

$$WARI = \frac{\sum_{i=0}^{N} RI_i \ Length_i}{\sum_{i=0}^{N} Length_i}$$ Equation 11

Where,

$WACI$ = System-level weighted-average condition index

$WARI$ = System-level weighted-average risk index

$Length_i$ = Length of Pavement Segment i

PCI_i = Condition index of Pavement Segment i

RI_i = Risk index of Pavement Segment i

N = Number of Pavement Segments considered in scenario

B.10 Preliminary Planning Scenarios and Trade-off Analysis

The multi-objective optimization model stochastically searches all possible combinations of pavement segments and feasible treatments to find a set of optimal solutions, each representing a candidate annual project list. The cost, benefit, and applicability rules of treatments are evaluated to identify the optimal solutions. A subset of the solutions that satisfy financial constraints and condition and risk targets are selected for further evaluation and trade-off analysis. The selected project list is then applied to update the condition of pavement segments for the following planning period. In multi-year scenarios, this analysis is repeated for every year. Resulting project lists are then used to quantify relationships between funding levels and system-level performance and risk measures.

The multi-objective optimization algorithm for pavement planning uses the pavement risk model to select projects, on a year-by-year basis, and optimize long-range investments by minimizing system-level risk at the lowest lifecycle cost. The algorithm has been implemented in our Asset Optimizer™ software. For more details on the algorithm, please refer to our previous report on bridge planning.

Based on the lifecycle and treatments models, we defined initial planning scenarios to assess the accuracy of these models, investigate the impact of varying budget levels, and estimate the financial requirements for maintaining the SHS pavement inventory over the next 10 years (2020-2030). These initial scenarios will be revised to align with Caltrans estimated funding and targets.

Two sets of preliminary scenarios were defined to determine annual project lists over 10-year planning horizon, which include: (1) Budget scenarios to assess the impact on system-level condition and risk levels; and (2) Target scenarios to evaluate budget requirements to achieve system-level performance and risk objectives. The initial scenarios defined are:

(1) A baseline Do-Nothing scenario to determine the impact of zero investment over 10-years (2020-2030).
(2) The current 4-year SHOPP scenario (2020-2023), assuming the planned SHOPP investment levels: $689 million, $586 million, $1.845 billion, and $1.387 billion.
(3) A 10-year budget scenario (2020-2030) that assumes the same SHOPP investment levels for the first 4-years (as in the previous scenario) and a fixed investment level for the remaining year similar to the level in 2023 ($1.387).
(4) Three 10-year budget scenarios (2020-2030), assuming fixed annual budget of $600 million, $800 million, and $1 billion.
(5) A condition target scenario to assess financial requirements to maintain status quo system-level condition index of 75, over 10-years (2020-2030), assuming unlimited budget.

No constraints were imposed on the budget splitting among different types of treatments. An average annual inflation rate was assumed to be 4% for all scenarios.

Scenario results show future condition and risk trends (in terms of system-level average condition and risk indices), detailed information on condition and risk measures of each pavement segment, as well as annual cost and work type of projects. The impact of each scenario on system-wide condition and risk levels was assessed and compared with other scenarios.

Figure 85 shows the system weighted-average condition and risk indices over the 10-year planning horizon under five different scenarios. Figure 86 shows a sample of predicted performance variables under various scenarios. The shown performance variables include cracking area percentage, IRI, cracking index, and roughness index. Figure 87 shows partial results for a typical scenario ($1 billion), showing the predicted average condition indices, FHWA performance measures, and total cost of projects by treatment type and by asset group. Figure 88 shows a map of the selected projects for the example $1 billion scenario.

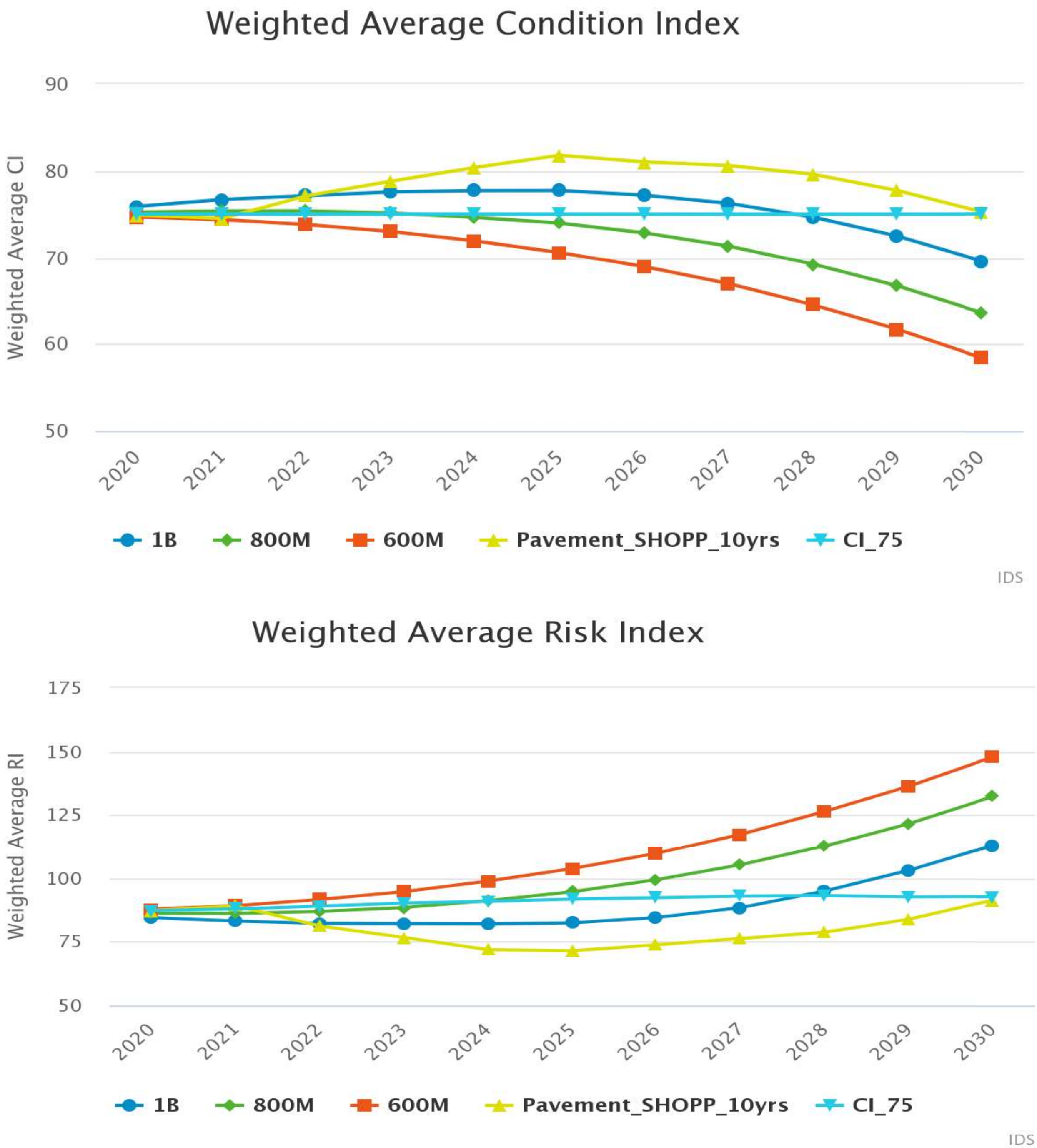

Figure 85. System-level average condition index (top) and risk index (bottom) under example planning scenarios.

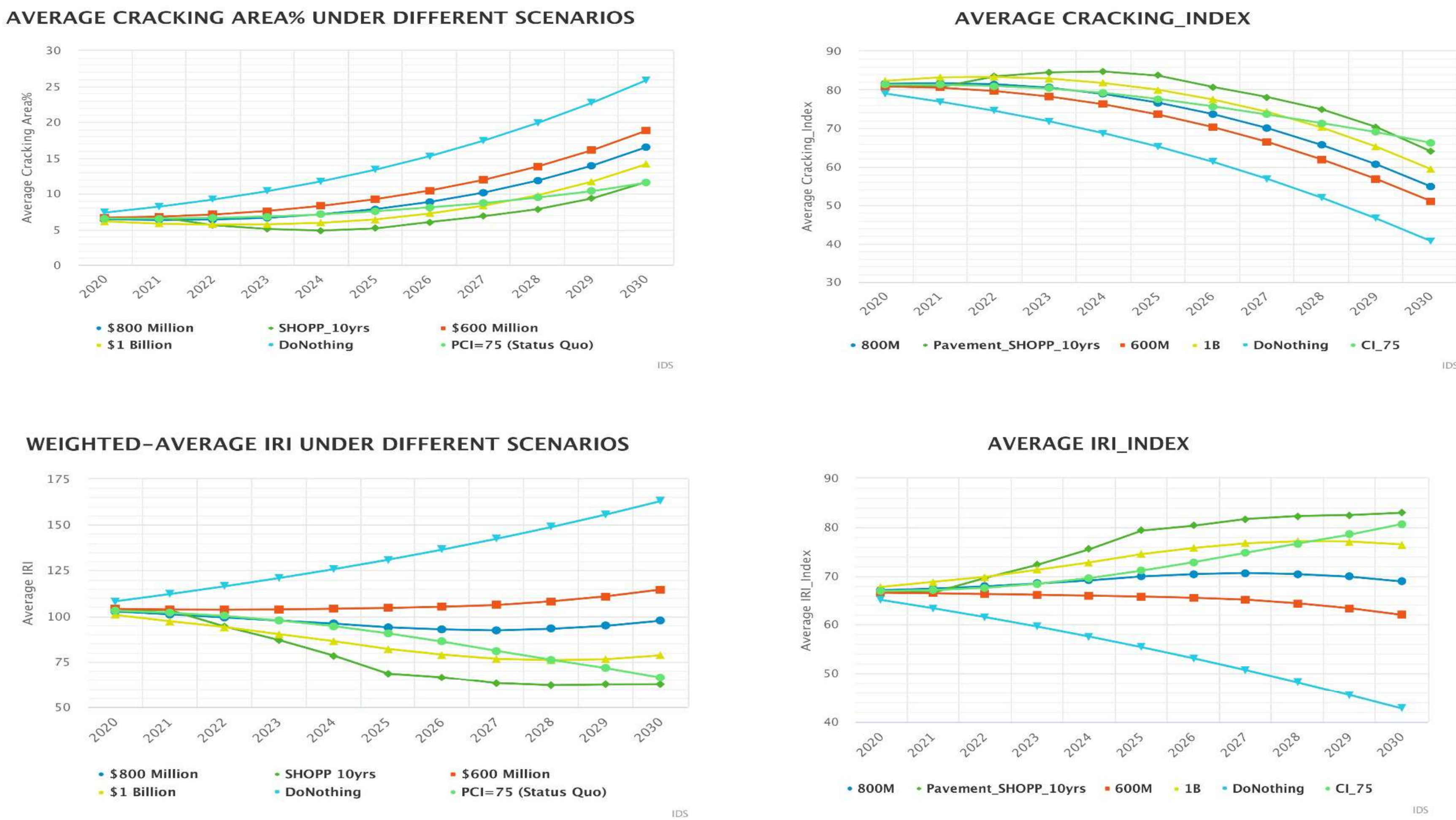

Figure 86. Cracking and roughness distresses and condition indices under example planning scenarios.

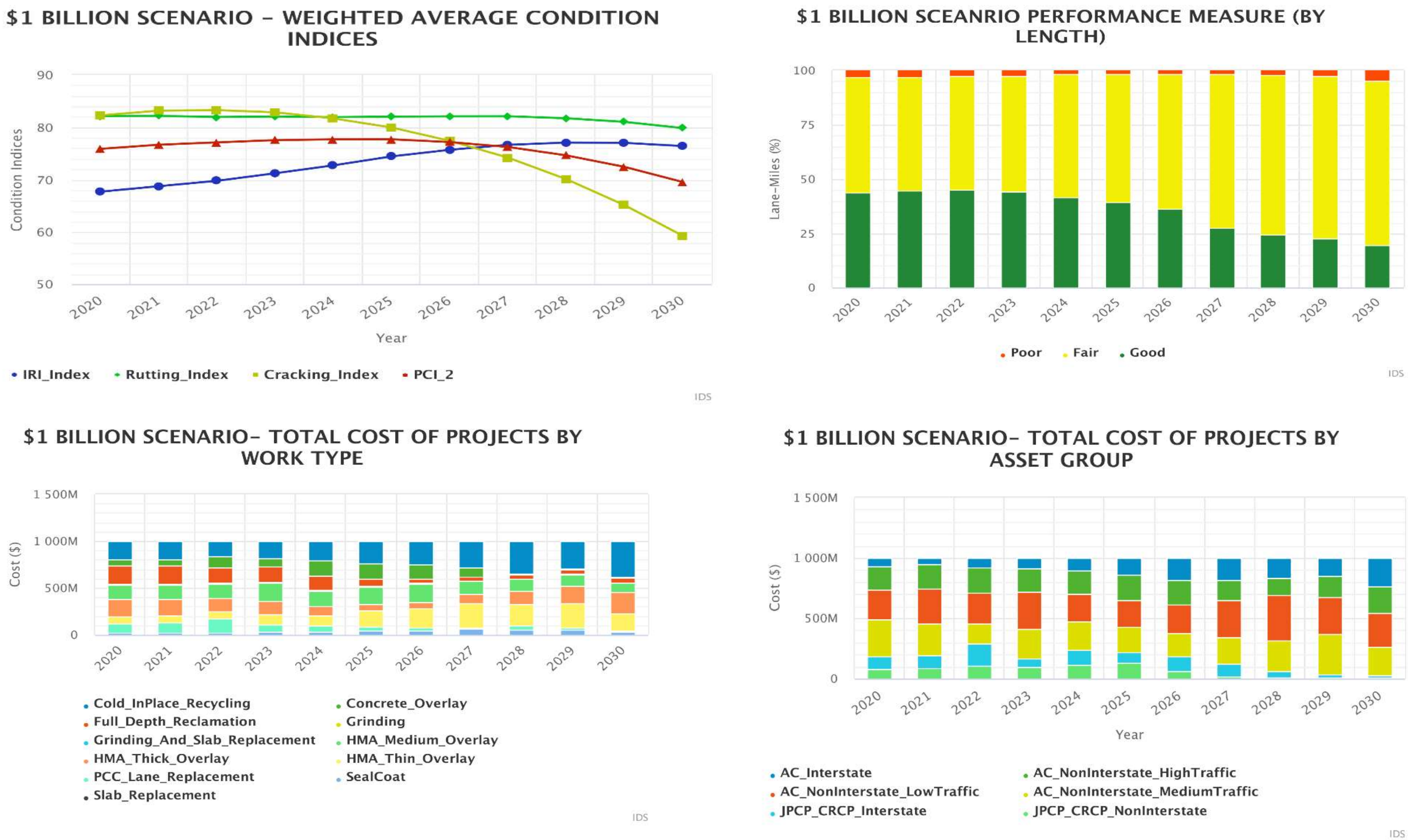

Figure 87. Example results of the $1 billion scenario showing average condition indices (top-left), performance measures (top-right), and total cost of recommended treatments by type (bottom-left) and group (bottom-right).

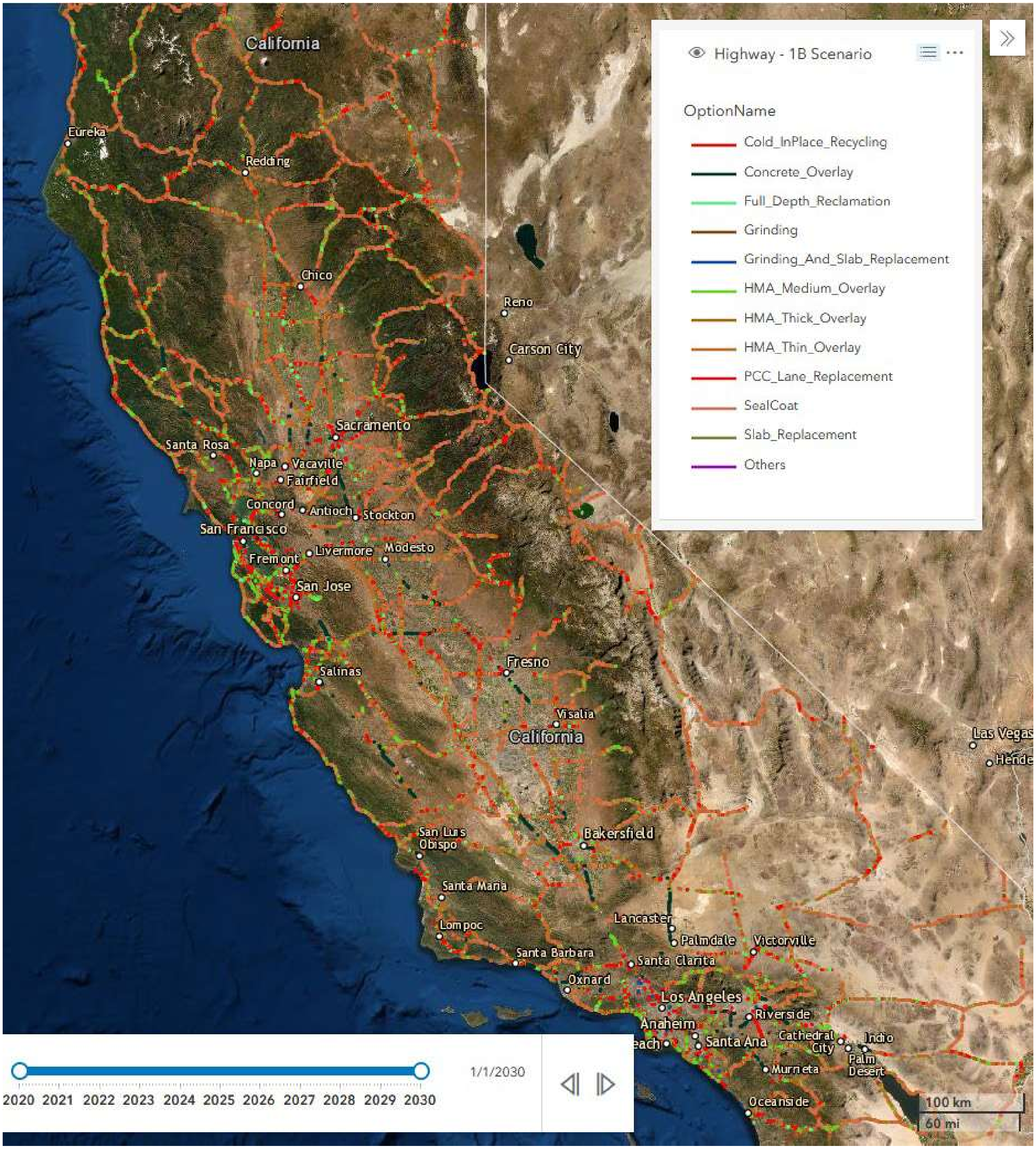

Figure 88. A map of 10-year pavement treatments selected under $1 Billion scenario

Appendix C:

Comparison of Optimization results and SHOPP Project Portfolio

An attached Excel workbook includes different tabs comparing the results of the optimization SHOPP 10-year scenarios and 2020 official SHOPP projects.