Stochastic Multi-Objective Optimization-Based Life Cycle Cost Analysis for New Construction Materials and Technologies

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This is the author's version of a work that has been accepted for presentation at the Transportation Research Board's 98th Annual Meeting, Washington D.C., 2019, and publication in the Transportation Research Record: Journal of the Transportation Research Board. The final version is available here: doi.org/10.1177/0361198119853578.

STOCHASTIC MULTI-OBJECTIVE OPTIMIZATION-BASED LIFE CYCLE COST ANALYSIS FOR NEW CONSTRUCTION MATERIALS AND TECHNOLOGIES

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Word count: 6,154 words text + 4 tables x 250 words (each) = 7,154 words
Resubmission Date: November 15th, 2018

Paper resubmitted for Presentation and Publication in the
Transportation Research Board's 98th Annual Meeting, Washington, D.C., 2019

ABSTRACT

The sustainability of transportation infrastructure depends on the adoption of new construction materials and technologies with great promise for improved performance and productivity. However, most agencies would like to evaluate these new materials and technologies at both project level and network level before replacing the traditional ones. It also remains a challenge to reliably estimate the costs and lifetime performance of new construction materials and technologies due to limited implementation data. To address these issues, this paper presents a comprehensive bottom-up methodology based on Life Cycle Cost Analysis (LCCA) to integrate project- and network-level analysis that can fast-track the acceptance of new materials or technologies. Hypothesized improvement rates are applied to the deterioration functions of existing materials to represent the expected improved performance of a new material compared with a conventional material with relatively similar characteristics. This new approach with stochastic treatment allows us to probabilistically evaluate new materials with limited data for their future performance. Feasible maintenance and rehabilitation schedules are found for each facility at the project level and near optimal investment strategies are identified at the network level by using a metaheuristic evolutionary algorithm while satisfying network-wide constraints. This provides an effective solution to many issues that have not been completely addressed in the past, including the trade-off between multiple objectives, effect of time, uncertainty and outcome interpretation. A hypothetical bridge decks system from New Jersey's bridge inventory database is used to demonstrate the applicability of the proposed methodology in construction planning and management decision support procedure.

Keywords: Bridge Management System, Life Cycle Planning, Life Cycle Cost Analysis, Probabilistic Multi-Objective Optimization

INTRODUCTION AND MOTIVATION

Aging facilities, growing technical and environmental demands, and increasing maintenance and repair costs have led agencies to seek development of innovative materials for construction and maintenance, as well as reliable decision-making tools for cost-effective transportation management and investments. The benefits of new materials or construction technologies may include: 1) providing cost-effectiveness and longer service life, 2) offering more efficient use of resources in construction operations, and 3) enabling the use of construction methodologies that will minimize construction duration and traffic delays. However, they may also bring new challenges, such as:

- Limited data availability: With no or very limited field implementation and historical data for new materials or construction technologies, accurately estimating cost and performance is challenging.
- High levels of uncertainties: There are many uncertainties due to the lack of reliable deterioration functions and time-dependent characteristics in life cycle cost (LCC) considerations. These uncertainties should be designated in the recently developed methodologies.
- Benefit in terms of “out-of-pocket” costs: A new construction material or technology may not bring direct cost savings. Instead, benefits may be reflected through indirect costs, such as decreasing work zone traffic delay or reducing air pollution or noise.

To evaluate the cost-effectiveness of such new materials or technologies, an effective economic-engineering solution, namely Life Cycle Cost Analysis, should be applied. Conducting Life Cycle Cost Analysis is a strategic decision-support approach for selecting the best strategies among feasible alternatives to achieve sustainability for the nation’s transportation infrastructure. At the project level, costs incurred during the lifetime of a transportation asset, including future maintenance and rehabilitation (M&R), delays in traffic, and social-economic impacts, should be considered. Network-level analysis that evaluates different combinations of projects and treatments to yield maximum benefits in developing cost-effective investment strategies is needed as well.

This paper presents research efforts on conducting LCCA for both conventional and new-technology materials to support decision making while considering agency, user, and social costs. The objective is to introduce a probabilistic bottom-up LCCA-based framework to meet project-level and network-level goals that not only work for conventional materials but also brand new construction materials and technologies for which actual performance data is limited. The framework includes stochastic treatment of the inherent uncertainties, quantification of benefits from new construction materials or technologies, including out-of-pocket costs and other externalities affecting environmental sustainability, and the integration of a project- and network-level optimization-based model framework. A combined project and network level approach should consider multiple performance measures and effect of time, deal with stochasticity and have clear outcome interpretation. Although there are studies in the literature that address one or two of these characteristics, our proposed methodology aims to provide a comprehensive solution to meet all three needs.

Moreover, the proposed approach will specifically try to provide a reasonable estimate of the future performance of the “new” construction materials or technologies based on their laboratory-measured data to overcome the challenge of limited data. Hypothesized improvement rates are applied to the deterioration functions of existing and well-known materials to represent the expected improved performance of a new material compared with a conventional material with relatively similar characteristics. In addition to the fixed rate improvement approach, our stochastic treatment is another way to account for the relatively higher uncertainties of new materials compared with the traditional ones. A case study is established using information based on the bridge inventory in New Jersey (NJ).

LITERATURE REVIEW

FHWA and State Highway Agencies (SHAs) recommend LCCA as an important technique for supporting transportation investment decisions. At the project level, numerous studies have applied LCCA to pavement and bridges. Some work *(1-6)* has been conducted comparing new construction materials or technologies with conventional ones. However, many of these studies used a deterministic approach *(1-3)* that did not reflect possible uncertainties involved in using new materials or construction technologies. Few of them consider uncertainties in service life or cost components. For example, Soliman and Frangopol *(5)* computed the bridge LCC using conventional painted carbon steel and corrosion-resistant maintenance-free steel. Though it had a higher initial cost, the maintenance-free steel was found to be more sustainable than conventional steel over the bridge's lifetime. Their study considered a probabilistic approach for the conventional material, however, the cost of maintenance-free steel is deterministic and the traffic growth is not capped over the 100-year analysis period. Eamon *et al. (6)* conducted both deterministic and probabilistic LCCA for bridge superstructures. Compare to traditional reinforcement materials and epoxy-coated steel, the new material, namely, carbon fiber reinforced polymer (CFRP) has a 95% probability to be the least expensive beginning at year 23–77 after initial construction. CFRP's expected service life was estimated based on experiences from other countries. The authors limited traffic growth by the bridge's maximum average annual daily traffic (AADT) and found that traffic volume has a significant effect on LCC. However, this study did not consider environmental impacts.

Network-level life cycle cost consideration is applied in various studies as well. National Cooperative Highway Research Program (NCHRP) Report 590 suggested a multi-objective network-level LCC model using Incremental Utility/Cost heuristic approach *(7)*. In 2017, The Asset Management Rule (the Rule) *(8)* required each state Department of Transportation (DOT) to perform "Network-level Life Cycle Planning" which is defined as "a process to estimate the cost of managing an asset class, or asset sub-group, over its whole life with consideration for minimizing cost while preserving or improving the condition" in compliance with the Moving Ahead for Progress in the 21st Century (MAP-21) and the Fixing America's Surface Transportation (FAST) Act. Based on NCHRP and the Rule, an ideal network-level model considering LCC is naturally a multi-objective optimization process that requires decision makers to evaluate the trade-offs between different conflicting objectives. It should take advantage of existing asset management system capabilities *(9)*, for instance, integrating project level information from existing databases to network level analysis. TABLE 1 synthesizes some of the studies on network-level optimization models over the past two decades. While not exhaustive, it provides a representative sample of recent research efforts. The purpose of Table 1 is to understand recent approaches used in for the network-level LCCA and to identify the research and development needs for applications involving new materials or technologies.

The majority of the studies in TABLE 1 are multi-objective optimization-based, which produces equally-good solutions known as a "Pareto Front" in which no alternatives can improve one or more objectives without making at least one objective worse. Different objectives can be either treated as separate functions without any preference before the optimization process *(10)*, or can be converted into a single-objective function (i.e. a single utility function) with subjective input *(11, 12)*. There's also an increasing trend of applying a probabilistic approach *(11, 13-15)* in the last decade to capture the uncertainties. For instance, Bryce *et al. (13)* demonstrated a network LCCA while treating the expected energy consumption probabilistically. They pointed out that a probabilistic approach should be used when the variable uncertainties may be significant. Although all studies incorporate agency cost, less than half considered user cost, and only three studies take social cost (i.e. from environment impacts) into account. In addition, some of the studies *(15-17)* considered project-level and network-level integration so information from existing asset management systems can be directly used as network-level inputs.

To summarize, a project-level LCCA model should be capable of quantifying the benefit and cost brought by the new materials or technologies, including agency, user and social costs, while an ideal network-level optimization model should consider multiple performance measures, effect of time, uncertainty, outcome interpretation, and integration between project- and network-level. Current practices meet one or some of the goals, but there is a need to develop a holistic and comprehensive tool that meets all of needs.

TABLE 1 Literature Review on Network-level Life Cycle Cost Models

Study	**Year**	**Asset Type**	**Objective(s)**	**Agency/User/Social Cost**	**Method**	**Time Frame**
Bryce *et al. (13)*	2014	Pavement	Min(maintenance cost), max(condition), min(energy consumption)	agency cost and social impact	Pareto front-based approach	3-year
Swei *et al. (14)*	2015	Pavement	Min(excess fuel consumption)	Only agency cost	Simple heuristic approach	15-year
Zhang *et al. (18)*	2012	Pavement	Min(life cycle energy consumption), min(GHG emissions), min(costs)	Agency and social cost	Backward Dynamic Programing	20-year
Marzouk & Omar *(11)*	2013	Sewer	min(cost), max(condition), max(extended network service life)	Only agency cost	Generic Algorithm	50-year
Liu & Frangopol *(10)*	2005	Bridge	Max(overall performance of a bridge network), min(maintenance cost)	Only agency cost	Generic Algorithm	30-year
Bukhsh *et al. (12)*	2018	Bridge	Max(condition index), min(agency cost), min(user delay cost), min (environmental cost)	Agency, user and social cost	Utility Theory	Not Applied
Yeo *et al. (15)*	2010	Pavement	Min(total system cost)	Agency cost	Generic Algorithm	40-year
Florida DOT *(16)*	2007	Bridge	Min(Life cycle cost)	Agency and user cost	Incremental benefit/cost algorithm	10-year
Indiana DOT *(19)*	2009	Bridge	Min(Overall benefits or effectiveness)	Agency and user cost	Dynamic/Integer linear programming /Markov chain	10-year

METHODOLOGY

Consider an infrastructure system composed of *n* independent facilities with different serviceability, traffic loads, etc. A "project candidate" in this study is defined as a life-cycle activity profile that contains a sequence of M&R activities for a transportation facility over certain analysis period. The proposed method aims to develop a two-level bottom-up approach based on LCC considerations. In the project-level, we first find "project candidates" -- all feasible M&R strategies for each facility based on project-level constraints, such as the facility's maximum traffic load or minimum acceptable serviceability and calculate the associated cost for each candidate. Secondly, we solve the network-level optimization to find the best combination of projects to meet network-level goals by choosing among project candidates found in the project-level model. Various economic and engineering models with optimization algorithms (i.e. Evolutionary Algorithm) are combined in the proposed approach to balance the trade-off between objectives and arrive at the optimum or near-optimum life cycle strategy. In addition, by connecting the two-level approach with an existing database as well as empirical deterioration models for the facilities, we are able to establish an integrated project- and network-level LCCA model framework as illustrated in FIGURE 1.

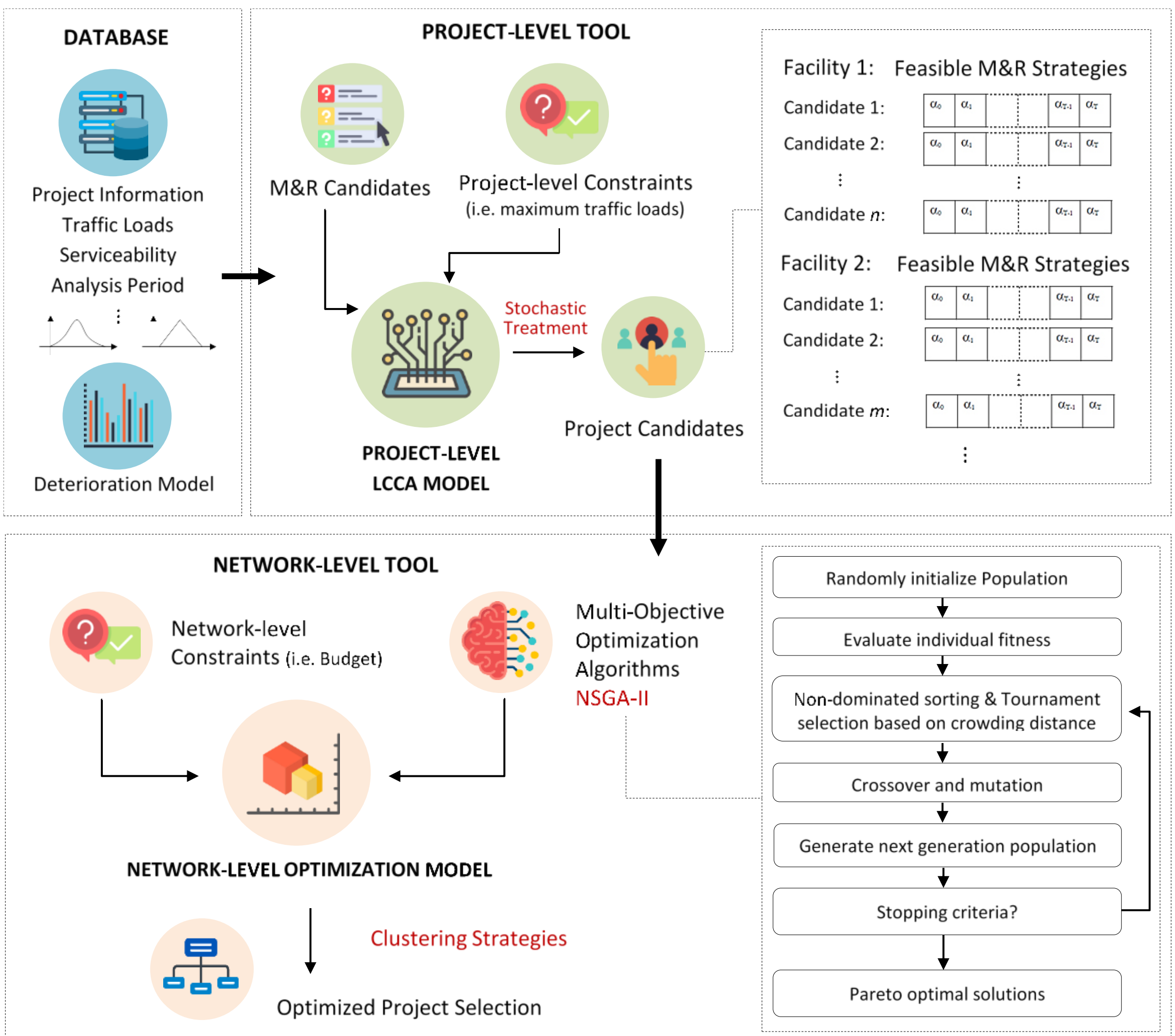


FIGURE 1 An integrated project- and network-level LCCA model framework.

Deterioration Model

The determination of cost-effective M&R actions demands accurate deterioration models that predict the anticipated future condition of transportation assets. Take a bridge deck as an example. The state of a bridge deck often is represented by discrete numbers such as the National Bridge Inventory (NBI) rating that describes the overall deck condition, ranging from 0 (Failed Condition) to 9 (Excellent Condition) *(20)*. In this study, empirical deterioration models for bridge decks in New Jersey were applied from a previous study *(21)* that uses NBI data for 2,438 bridges located on interstates, US numbered and state highways. A third order polynomial regression model (Equation 1) is fitted based on the assumption that the downgrade of condition rating represents the deterioration of the bridge deck *(21)*. The regression results and more details can be found in *(21)*. These deterioration models are used as the baseline for conventional construction materials or technologies.

$$CR = M_0 + M_1 x + M_2 x^2 + M_3 x^3 \tag{1}$$

where CR is the bridge condition rating, and regressor x is the age of deck in years. M_0, M_1, M_2, and M_3 are the parameters.

However, it is not a simple task to predict the actual field performance of a brand-new construction material or technology that has either only been tested in a laboratory environment or undergone a very limited field deployment. A hypothesized improvement rate approach is proposed in this study to link the deterioration functions of existing and well-known materials to represent the expected enhanced performance of a new material compared with a conventional material with relatively similar characteristics. It is assumed that the deterioration function of the new material will follow a similar "pattern" as that of the well-known conventional material. However, this pattern will be shifted to represent the enhanced performance of the new material (Equation 2). The laboratory improvement rate estimated from a combination of performance measures (i.e. compressive strength and cracking resistance), which is denoted by β, can be a single fixed value that is most likely to occur (deterministic approach) or a distribution (probabilistic approach). The correlation factor k is applied to generate estimates when applying laboratory improvement rate to field. The improvement rate can be applied to all or part of the deterioration function. For instance, if the new material has a significant improvement in terms of increasing the crack and propagation resistance for bridge decks, the estimated improvement rate may be applied to Stage 1 (condition rate 9-6) of the deterioration model. FIGURE 2 shows an example that turns results from laboratory tests into the improvement rate by employing this approach.

$$F(x) = k \cdot f(\beta x) \tag{2}$$

Where $F(x)$ = New material deterioration function

$f(x)$ = Conventional material deterioration function

β = Deterministic or probabilistic laboratory improvement rate

k = Correlation factor when applying laboratory improvement rate to field

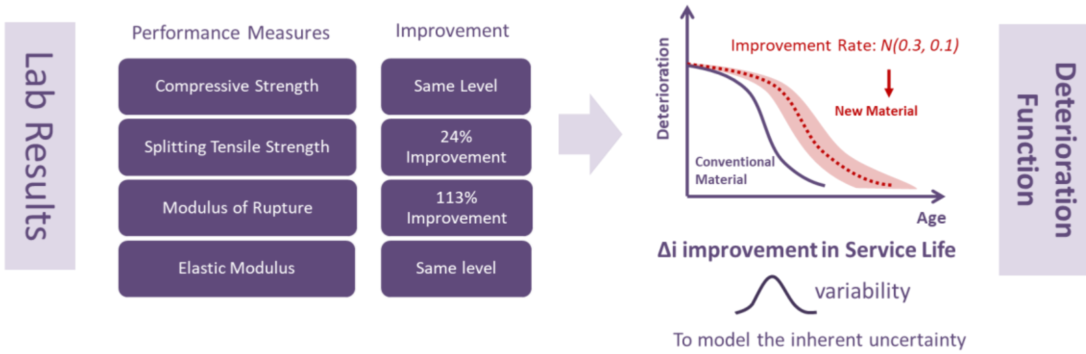


FIGURE 2 Using laboratory results to update a deterioration function: an example.

Project-level LCCA Model

Let's denote *t* as the year and *T* as the analysis period. $a_t \in \{0,1,2...m\}, \mathrm{m} \in \mathbb{Z}$ is a non-negative integer representing the type of M&R activity to be scheduled at year *t*. a_t equals zero if no activity is to take place that year. For example, if bridge project A has three types of activities (0,1,2) that stands for "no action" "repair" and "replacement", then $a_{20} = 2$ means at year 20, a type 2 activity "replacement" is scheduled. The M&R strategy for a project becomes a sequence of a_t.

The proposed project-level LCCA model considers three cost components: agency cost, user costs and social cost. User cost in the proposed methodology includes a Traffic Delay Cost (TDC) model using deterministic queueing approach *(22)*, a Vehicle Operation Cost (VOC) adopted from NCHRP Report 133 method and FHWA's guideline on work zone road user costs *(23)*, and a Crash Risk Cost (CRC) model *(24, 25)*. Social cost (SC) has an air pollution module *(26)* and can be extended to include other costs from noise or energy consumption. Only the differential user and social costs occurring during work zone periods are considered in this approach. Weights are assigned to different costs to mimic the actual decision-making process used in many agencies where the agency costs usually get the highest weight *(27)*. For each M&R strategy *j* of facility *i*, its net present value (NPV) is calculated as follows:

$$\mathrm{NPV} = \sum_{t=0}^{T} \frac{w_1(AC_t(a_t) - \mathrm{SV}_t) + w_2(TDC_t(a_t,V_t) + VOC_t(a_t,V_t) + CRC_{(t)}(a_t,V_t)) + w_3 \cdot SC_t(a_t,V_t)}{(1+r)^t} \quad (3)$$

Where,

t = the year at which the cost is incurred (years)

T= analysis period (years)

r = discount rate (decimals)

a_t = a non-negative integer representing the type of maintenance & rehabilitation (M&R) activity to be scheduled at year *t* and equals to zero if no M&R action is to take place, a_t is bound by deterioration function $f(CR_t)$, where CR_t is the condition rate at year *t*.

V_t = AADT at year *t* (vehicles/day) and $V_t \leq Max$(AADT)

$AC_t(a_t), TDC_t(a_t,V_t)$, $VOC_t(a_t,V_t)$, $CRC_t(a_t,V_t)$, $SC_t(a_t,V_t)$ are the agency cost, traffic delay cost, vehicle operation cost, crash risk cost, and social cost at year *t* ($); all are dependent on M&R activity a_t. Traffic delay, vehicle operation, crash risk, and social cost are also subject to traffic volume V_t

SV_t = the salvage value, it only occurs at the end of the analysis period T ($)

w_1, w_2, w_3 are the weight factor of agency cost, user cost, and social cost

Since the technical performance, initial construction cost, timing and cost of M&R activity, and disposing of a new-material structure are usually less certain than those for conventional materials, these variabilities can greatly affect the final solutions. Therefore, stochastic treatments - Monte Carlo simulations are applied when calculating all cost components. The final output of the project-level tool is a set of feasible project candidates that contains a sequence of M&R activity a_t and associated costs. It is worth mentioning that different candidates of the same facility may have the same type of M&R activities, but because these activities are scheduled for different years, their costs will be different. Traffic growth is bounded by the maximum allowable traffic that can pass through the facility, so this value cannot grow infinitely and lead to unrealistic user or social cost. Furthermore, the maximum allowable year for the first rehabilitation/replacement action depends on the minimum acceptable serviceability of the facility– if a facility's estimated serviceability at year *t* is less than a certain threshold, a rehabilitation/replacement activity is assumed to be scheduled immediately for the next year *t+1*. Each candidate after this year becomes infeasible. Consequently, each facility has a different number of feasible candidates.

Network-level Multi-Objective Optimization Model

Assuming that all facilities are independent and given a set of constraints (i.e. budget), the network-level optimization can be formulated as a multi-choice, multi-dimensional knapsack problem (MCMDKP). Let's denote $M_i = \{0,1,2,...\}$ to be the feasible project candidates for facility i where $1 \le i \le n$. x_{ij} is the decision variable and equals to 1 if candidate j of facility i is selected ($j \in M_i$). Two objectives are considered in this study. The first objective is to minimize the total LCC of selected project candidates. The second objective is to consider facility importance. For example, bridges carrying heavier traffic may get higher priority than others as they are more sensitive to potential failure. Therefore, traffic loads are used to represent facility importance. Both objectives are normalized so they are comparable. The network-level optimization problem can be formulated as follows:

$$\text{Minimize} \sum_{i=1}^{n} \sum_{j \in M_i} NPV_{ij} x_{ij} \tag{4}$$

$$\text{Maximize} \sum_{i=1}^{n} \sum_{j \in M_i} AADT_i x_{ij} \tag{5}$$

Subject to:

$$B_l \le \sum_{i=1}^{n} \sum_{j \in M_i} AC_{ij} x_{ij} \le \mathrm{B}_u \tag{6}$$

$$\sum_{j \in M_i} x_{ij} \le 1, \quad (1 \le i \le n) \tag{7}$$

$$\sum_{i=1}^{n} \sum_{i \in M_i} x_{ij} \le S \tag{8}$$

$$x_{ij} = 0 \text{ or } 1 \tag{9}$$

Where,

$x_{ij} = 1$ if candidate *j* of bridge *i* is selected, $x_{ij} = 0$ otherwise.

NPV_{ij} = Net Present Value of candidate *j* for bridge *i*

$AADT_i$ = Current annual average daily traffic of bridge *i*

CR_{0i} = Current condition rating of bridge *i*

AC_{ij} = Agency cost of candidate *j* for bridge *i*

B = Budget ($)

S = Maximum number of candidates selected

NCHRP Report 590 *(7)* pointed out that besides a budgetary ceiling, considering a minimum budget is also necessary in the optimization problem. Hence, a lower bound of the budget is considered to ensure at least a certain percentage of the budget will be utilized. In addition to the monetary limitation, a maximum number of selected project candidates are determined in Equation (8) to represent agency resource limitations (i.e. maximum number of construction contractors an agency can have in a certain time horizon). Equation (7) is to make sure every facility will have only one project candidate (a sequence of M&R actions) selected.

Various optimization algorithms have been applied in long-term infrastructure management such as linear programming or dynamic programming. Evolutionary algorithms like Generic Algorithm (GA) based on Darwin's evolution theory have also gained recognition in many engineering applications. For the proposed network-level optimization model, the Non-dominated Sorting Genetic Algorithm II (NSGA-II) *(28)* is employed to obtain the Pareto optimal solutions. Steps of NSGA-II can be found in FIGURE 1. NSGA-II has been proven to be an efficient Multi-objective evolutionary algorithm that maintains population diversity and excellent individuals *(29)* and has been used in transportation asset management *(30)*.

However, instead of a single solution, multi-objective optimization usually produces many equally good solutions, making it complicated to interpret the outcome. Furthermore, each managing agency may have additional performance measures besides minimizing cost and giving priority to important facilities. To solve these problems, we propose to have one more step after getting the Pareto-optimal solutions – applying multiple clustering strategies based on additional preferences. Additional preferences may include network-level serviceability requirement, less risky selections or best utilization of the budget. The best solutions from each cluster will give decision makers clearer insight into the outcome and narrow down the selections to a few optimal and sub-optimal solutions.

CASE STUDY

The following section illustrates an application of the proposed stochastic multi-objective optimization using a conventional concrete and an advanced material—fiber reinforced self-consolidating concrete (FR-SCC)—material for bridge decks. Self-consolidating concrete (SCC) can decrease construction time, labor, and equipment needed on construction sites and reduce noise impact and injuries related to vibration work of concrete *(31)*. Fiber reinforcement can extend the technical benefits of SCC by providing crack bridging ability, higher toughness, and long-term durability. Based on the potential benefits of the FR-SCC, the following assumptions are applied in the case study *(32, 33)*:

- Based on a combination of laboratory improvements including compressive strength, modulus of elasticity, shrinkage, durability factor, and cracking resistance, probabilistic distribution of a hypothetical improvement rate is applied on the conventional material deterioration curve to Stage 1 (condition rate 9-6) of deck deterioration to represent the estimated deterioration curve of FR-SCC (FIGURE 3).

- The material unit cost is approximately \$91.05/CY for conventional concrete and \$106.5/CY for the FR-SCC mix used in this study *(33)*. The new material is assumed to have higher uncertainty in terms of material and construction unit cost and expected service life.
- Since no vibration is required *(34)*, SCC is possible to shorten construction duration so a 10%-15% time saving is suggested for rehabilitation activities.
- The placement and consolidation labor costs will be reduced by using SCC *(35)*, thus a 20% saving in the labor cost is assumed when estimating FR-SCC construction unit cost.

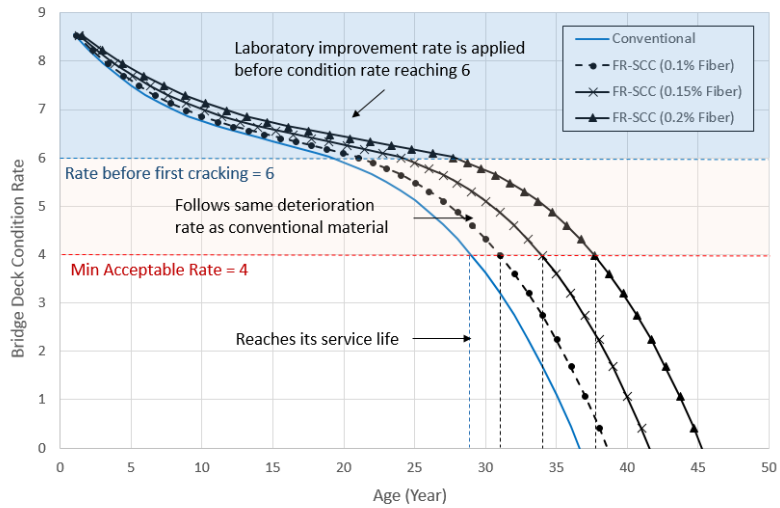


FIGURE 3 Deterioration curve for new material on highway Interstate-80.

The traffic, structure, and current deck condition rate information for 10 bridges (TABLE 2) is obtained from a unified database of New Jersey Bridge Management System and Inventory *(36)*. The service life of these bridges using conventional concrete is estimated from the empirical model described in the previous section. Average Daily Traffic (ADT) values are used as an approximation of AADT values. In this case study, normal and triangular distributions are assumed for five parameters whose uncertainties are significant: 1) new material improvement rate: $N(45.5\%, 25\%)$, 2) service life: Conventional Concrete (year): $Tri(27,31,29)$, FR-SCC (year): $Tri(33,43,38)$, 3) traffic growth: $N(1.0\%, 0.5\%)$, 4) construction unit cost: Conventional Concrete (\$/SF): $N(167,5)$, FR-SCC (\$/SF): $N(171.5,20)$, and 5) discount rate: $N(3.0\%, 0.5\%)$ *(33)*. Monte Carlo simulations are applied to perform random sampling from these probability distributions. A weighted factor for user cost (0.3 in this example) is applied when calculating LCC.

TABLE 2 Bridge and traffic information for 10 bridges in New Jersey

ID	Route	Year Build	Number of Lanes	ADT (vehicles/ day)	Deck Length (ft)	Deck Width (ft)	Condition Rate	%ADT Truck	Service Life* (year)
0	I-78	1965	4	39,135	39.3	23	4	9	29
1	US-322	1924	2	23,685	6.1	10	4	4	53
2	US-80	1959	3	66,400	32.9	17.5	6	9	31

3	US-9	1925	2	20,660	7.9	13.4	3	4	48
4	NJ-15	1900	2	31,625	15.5	14.2	4	4	86
5	US-46	1933	4	8,430	53	27.8	4	7	44
6	US-22	1931	4	68,880	163.1	28.5	4	4	56
7	US-1	1928	4	44,900	262.7	12.9	3	4	39
8	I-280	1972	3	39,730	320.7	13.7	4	9	41
9	I-280	1950	1	4,000	41.8	9.1	4	9	41

*Service life using conventional concrete: estimated from the empirical deterioration model *(21)*.

After getting all feasible project candidates from project-level LCCA model, NSGA-II-based procedure is then applied on the network-level. 100 probabilistic runs with 50 NSGA-II generations in each run are generated. The time horizon is assumed to be 75 years for LCC calculations, and year-10 evaluation of average network conditional rate is computed as an additional network-level performance measure. The total agency budget is set at 3 million dollars. For demonstration purposes, only two M&R actions (do nothing and rehabilitation) for the bridge deck are considered in the network-level model.

RESULTS, DISCUSSIONS AND LIMITATIONS

Project-level LCCA Results

Let's use the first four digits to represent the bridge ID and the next two digits to represent the year of the first rehabilitation activity, for example, "bridge 0 – year 1" project candidate is denoted as ('0000','01'). The total LCC of two alternatives for this project candidate is represented using Probability Density Function (PDF) and Cumulative Distribution Function (CDF). FIGURE 4 shows the output of the project-level LCCA model for a single project candidate using bridge 0 information from TABLE 2 with a first rehabilitation activity at year 1. The results indicate the FR-SCC alternative is less expensive ($0.341 million) compared with the conventional concrete ($0.383 million) in terms of their mean LCC values. However, FR-SCC also has more uncertainty (a wider distribution) with a standard deviation of $0.045 million compared to that of the conventional material, which is $0.031 million. If we investigate the cost component separately, the application of the new material saves 10.6%, 42.9%, and 37.5% for agency costs, user cost, and social cost in terms of their main values, respectively. Although the agency cost saving is not significant, the benefit of using FR-SCC in user costs and potential environmental savings play an important role and should not be ignored. Each project candidate is evaluated probabilistically via multiple runs and these cost values are then passed into the network-level optimization model.

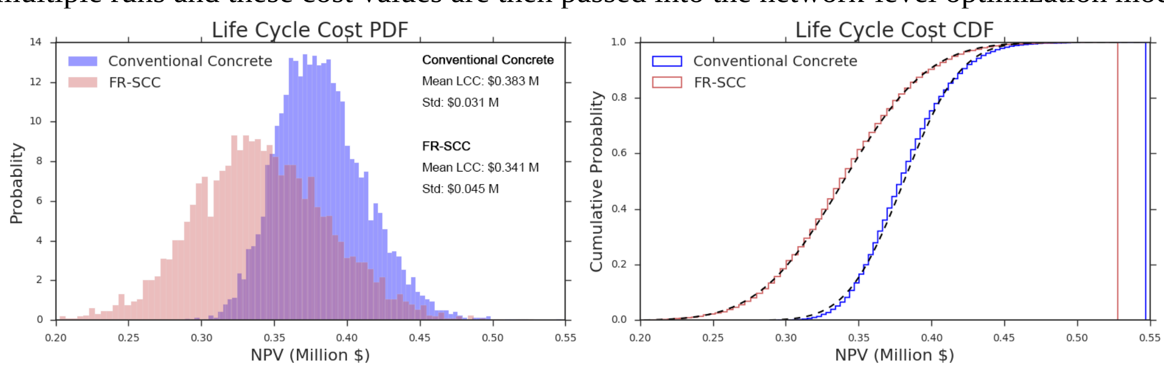
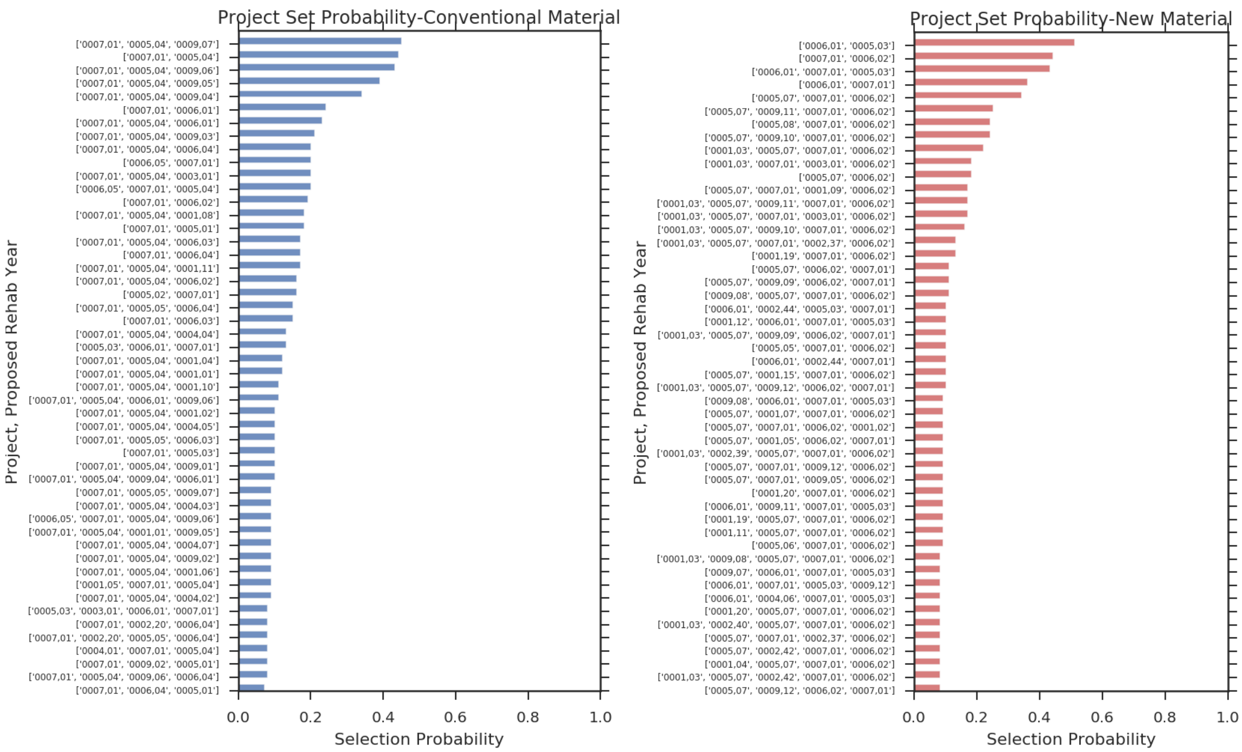


FIGURE 4 PDF and CDF of the LCC for conventional concrete and FR-SCC for project candidate ('0000', '01').

Network-level Optimization Results

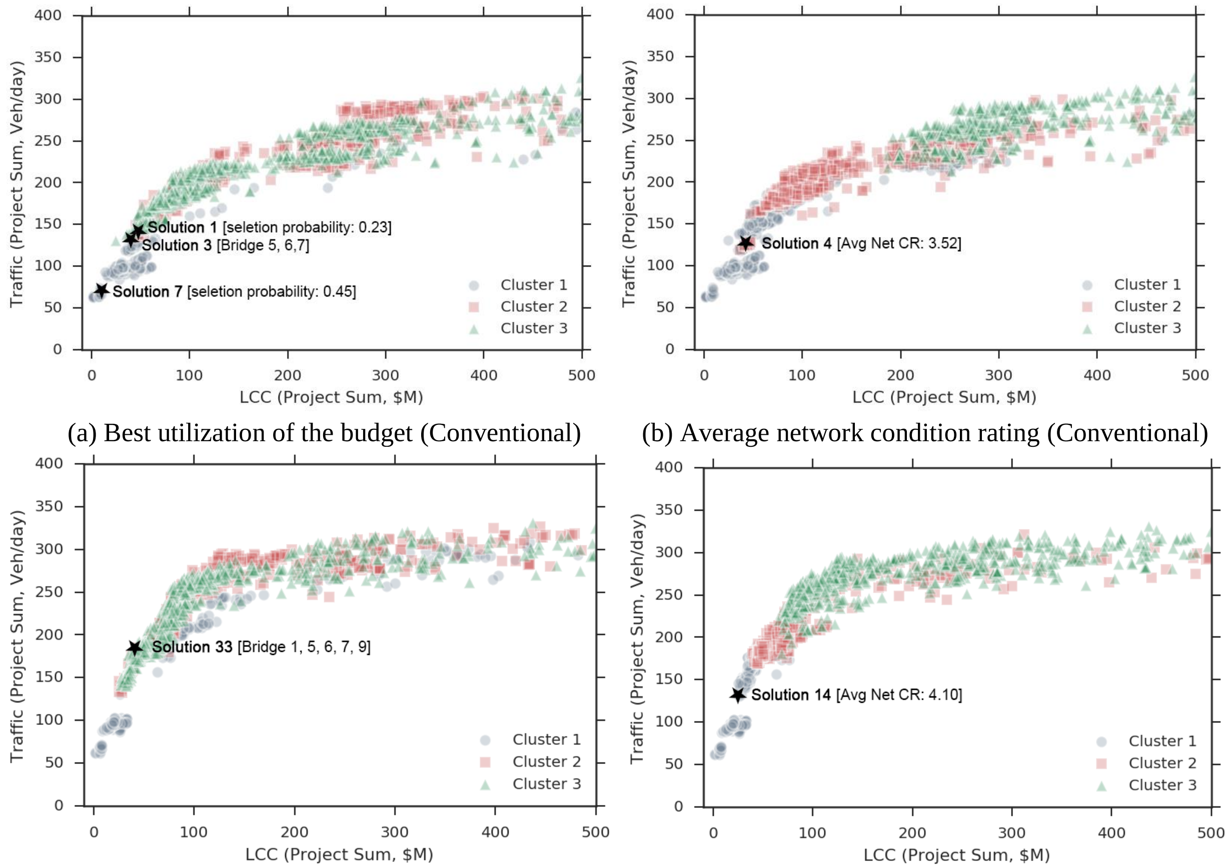
For each probabilistic run, the network-level optimization model generates various pareto-optimal solutions where each solution is a combination of different project candidates. Due to the stochasticity of input parameters and the NSGA-II searching procedure, the pareto-optimal solutions of each run may be different. The final network-level optimization model output contains all pareto-optimal solutions that ever exist in any of the runs and their selection probabilities are computed. Selection probability indicates how many times this solution is selected as a pareto-optimal solution during all probabilistic runs. A solution with lower selection probability means a relatively riskier solution in comparison to a solution with higher selection probability. The final model generates 2,335 and 2,399 pareto-optimal solutions for the 10 bridges in TABLE 2 using conventional concrete and FR-SCC, respectively. FIGURE 5 presents the first 50 solutions ranked by their selection probabilities for each alternative.



(a) Conventional Concrete (b) FR-SCC

FIGURE 5 Network-level optimization model results.

Next, two clustering strategies are applied to better interpret the results. The first strategy is to best utilize the available budget, so the remaining budget is minimized. The second strategy is to maximize the average network bridge deck condition rate (evaluated at the end of year 10 consider a planning horizon), so it can meet the agency's performance goals. An efficient unsupervised learning algorithm, K-means, is used to cluster the pareto-optimal solutions into three clusters. FIGURE 6 illustrates the graphic representation of the clustering results. Network performance measures of the top three solutions (project sets) in each cluster are listed in TABLE 3 and TABLE 4 including selection probability, total agency cost, total life cycle cost, total traffic loads, average bridge network condition rating and remaining budget. The results are for the mean condition - the average of the stochastic variables.



(a) Best utilization of the budget (Conventional) (b) Average network condition rating (Conventional)

(c) Best utilization of the budget (FR-SCC) (d) Average network condition rating(FR-SCC)

FIGURE 6 Clustering results.

With conventional material, for example, if a decision maker's additional preference is to best utilize all budget, he or she should focus on solutions in the clustering strategy "budget" (solution 1 to 9). Solution 1 in budget cluster 1 (Bridge 5 with its first rehabilitation at year 4, Bridge 6 and 7 with their first rehabilitation at year 1) can be a good candidate since it has the minimum remaining budget of 0.17 million dollars. However, as the selection probability of this candidate is relatively low (0.23), in certain cases, decision makers might opt for less risky alternatives even if the mean value is higher. Under this circumstance, solution 7 in budget cluster 3 may be a good alternative. Our findings also provide additional support of FR-SCC's benefit on the network-level. For similar budget levels and selection probability, FR-SCC allows decision makers to select more bridges. For example, solution 3 and 33 both have similar budget levels ($2.66 Million and $2.62 Million) and selection probabilities of 0.20 and 0.16, respectively. Solution 33 using FR-SCC allows to rehabilitate two more bridges compared with solution 3 which uses conventional material. Moreover, using FR-SCC is relatively cheaper and maintains a better average network level condition rate for the same project combination (i.e. solution 4 and 14).

TABLE 3 Clusters Based on Remaining Budget – Top Three Solutions in Each Cluster

Budget Cluster	#	Project Set (‘project ID’, ‘first rehabilitation year’)	Selection Prob	Total Agency Cost ($M)	Total LCC ($M)	Total Traffic (1000vehs/day)	Avg Net CR	RMNG budget ($M)
Conventional Concrete								
1	1	['0007,01', '0005,04', '0006,01']	0.23	2.83	47.86	146.51	4.09	0.17
	2	['0007,01', '0005,04', '0006,04']	0.20	2.68	50.55	145.99	4.13	0.32
	3	['0006,05', '0007,01', '0005,04']	0.20	2.66	44.38	142.87	4.15	0.34
2	4	['0006,01', '0007,01']	0.24	2.38	47.84	135.70	3.52	0.62
	5	['0006,05', '0007,01']	0.20	2.24	42.10	132.82	3.58	0.76
	6	['0007,01', '0006,02']	0.19	2.36	47.42	135.34	3.54	0.64
3	7	['0007,01', '0005,04', '0009,07']	0.45	1.63	8.08	67.71	4.17	1.37
	8	['0007,01', '0005,04']	0.44	1.53	1.56	63.00	3.57	1.47
	9	['0007,01', '0005,04', '0009,06']	0.43	1.63	8.20	67.78	4.15	1.37
FR-SCC								
1	10	['0006,01', '0007,01', '0005,03']	0.43	2.59	28.10	149.48	4.63	0.41
	11	['0005,07', '0007,01', '0006,02']	0.34	2.51	28.55	146.77	4.69	0.49
	12	['0005,07', '0009,11', '0007,01', '0006,02']	0.25	2.59	33.86	152.04	5.29	0.41
2	13	['0007,01', '0006,02']	0.44	2.16	28.22	137.49	4.11	0.84
	14	['0006,01', '0007,01']	0.36	2.22	27.67	139.20	4.10	0.78
	15	['0001,03', '0007,01', '0003,01', '0006,02']	0.18	2.19	59.75	194.38	5.23	0.81
3	16	['0006,01', '0005,03']	0.51	1.61	26.96	94.90	4.02	1.39
	17	['0005,07', '0006,02']	0.18	1.55	27.64	94.19	4.08	1.45
	18	['0005,08', '0006,02']	0.07	1.53	26.94	92.07	4.10	1.47

TABLE 4 Clusters Based on Average Network CR – Top Three Solutions in Each Cluster

NetCR Cluster	#	Project Set (‘project ID’, ‘first rehabilitation year’)	Selection Prob	Total Agency Cost ($M)	Total LCC ($M)	Total Traffic (1000vehs/day)	Avg Net CR	RMNG budget ($M)
Conventional Concrete								
1	19	['0006,05', '0007,01', '0005,04', '0002,22', '0009,04']	0.01	2.92	186.37	217.24	5.76	0.08
	20	['0007,01', '0005,05', '0002,23', '0006,03', '0009,07']	0.01	2.88	186.91	231.34	5.87	0.12
	21	['0007,01', '0005,04', '0006,03', '0002,24', '0001,04']	0.01	2.81	192.14	253.34	5.87	0.19
2	22	['0005,03', '0009,03', '0006,01', '0007,01', '0003,01']	0.03	2.89	77.24	183.82	5.22	0.11
	23	['0005,03', '0007,01', '0009,04', '0006,01', '0003,01']	0.03	2.89	80.78	183.60	5.23	0.11
	24	['0001,05', '0005,03', '0006,01', '0007,01', '0003,01']	0.03	2.79	92.78	208.71	5.22	0.21
3	25	['0007,01', '0005,04', '0009,07']	0.45	1.63	8.08	67.71	4.17	1.37
	26	['0007,01', '0005,04']	0.44	1.53	1.56	63.00	3.57	1.47

	27	['0007,01', '0005,04', '0009,06']	0.43	1.63	8.20	67.78	4.15	1.37
FR-SCC								
1	28	['0001,03', '0005,07', '0007,01', '0002,37', '0006,02']	0.13	2.57	106.48	258.94	6.45	0.43
	29	['0006,01', '0002,44', '0005,03', '0007,01']	0.10	2.60	80.41	231.85	6.27	0.40
	30	['0001,03', '0002,39', '0005,07', '0007,01', '0006,02']	0.09	2.58	98.29	255.42	6.55	0.42
2	31	['0001,03', '0005,07', '0009,11', '0007,01', '0006,02']	0.17	2.61	48.48	182.11	5.80	0.39
	32	['0001,03', '0005,07', '0007,01', '0003,01', '0006,02']	0.17	2.55	60.87	203.81	5.82	0.45
	33	['0001,03', '0005,07', '0009,10', '0007,01', '0006,02']	0.16	2.62	49.34	183.41	5.80	0.38
3	34	['0006,01', '0005,03']	0.51	1.61	26.96	94.90	4.02	1.39
	35	['0007,01', '0006,02']	0.44	2.16	28.22	137.49	4.11	0.84
	36	['0006,01', '0007,01', '0005,03']	0.43	2.59	28.10	149.48	4.63	0.41

While the aim of the study is achieved, the current approach has limitations. Firstly, applying a constant traffic growth rate or a growth rate with a same distribution over the whole analysis period does not reflect real-world conditions and may overestimate user costs when using deterministic queueing model. Instead, a multi-stage traffic growth rate can be applied. For example, New York City (NYC) suggests a 0.25% traffic growth rate for year 1 to 5, and 0.125% from year 6 and beyond *(37)*. Secondly, including the effect of more M&R strategies such as Preventive Maintenance (PM) and defining reliable probabilistic distribution of input parameters are needed as future research efforts as well.

CONCLUSIONS

This paper presented an integrated bottom-up stochastic LCCA-based approach for finding feasible M&R strategies at the project level and optimizing best project selection for transportation infrastructure network. A probabilistic multi-objective framework is proposed for conventional and innovative construction material and technologies. A hypothetical improvement rate method with stochastic treatment is developed based on an empirical deterioration model of known material to provide a reasonable estimate of the performance for the new construction material and technology. Use of this new approach to evaluate new materials with limited data for the development of deterioration functions allows us to account for the relatively higher uncertainties of new materials compared with the traditional ones.

Besides quantification of benefits from new construction materials or technologies, this study further contributes to the literature by providing a holistic and comprehensive approach that meets the following needs: 1) to support multi-objective decision making while considering time effect and agency, user, and social costs, 2) to provide stochastic treatment of the inherent uncertainties, 3) to establish an integration of a project- and network-level optimization-based model framework, and 4) to provide clear outcome interpretation.

The project-level LCCA model extracts facility information from an existing database and produces feasible project candidates with their associated M&R activities and costs. Besides agency cost, user and social cost are also included when computing project LCC. The network-level optimization model is formulated as a MCMDKP and is solved by using an evolutionary algorithm, NSGA-II, to identify near-optimal solutions that balance the trade-offs between minimizing LCC and maximizing traffic loads of selected projects. Stochastic treatment of input parameters with high uncertainties provides us with a risk-based asset management approach that is more versatile and comprehensive than deterministic LCCA when it comes to making long-term decisions. In addition, clustering strategies are integrated into the decision process to enhance the traditional multi-objective LCCA by adding the capability of partitioning the pareto-optimal solutions based on additional preference. Finally, a case study is presented to demonstrate the applicability of the proposed approach in selecting near-optimum solutions for a bridge network. Though with a higher material and construction cost, FR-SCC was found to be more sustainable than conventional concrete over the lifetime of bridge decks on both project-level and network-level.

As an ongoing research effort, the proposed method will be integrated into an easy-to-use web-based application with multi-stage traffic growth rate, different M&R strategies and more reliable probabilistic distribution of input parameters.

ACKNOWLEDGMENTS

The work in this paper is sponsored by RE-CAST University Transportation Center (UTC) led by Missouri University Sicence and Technology and C2SMART, a Tier 1 UTC at New York University. Both UTCs are funded by U.S. Department of Transportation. The authors acknowledge Peng Lou and Giuseppe Liberti from Rutger University and Iman Mehdipour and Ahmed abdelrazik from Missouri University Sicence and Technology for sharing FR-SCC data. The contents of this paper only reflect views of the authors who are responsible for the facts and do not represent any official views of any sponsoring organizations or agencies.

AUTHOR CONTRIBUTION STATEMENT

The authors confirm contribution to the paper as follows: study conception and design: Jingqin Gao, Kaan Ozbay, Hani Nassif; data collection: Jingqin Gao, Onur Kalan; analysis and interpretation of results: Jingqin Gao; draft manuscript preparation: Jingqin Gao, Kaan Ozbay, Hani Nassif. All authors reviewed the results and approved the final version of the manuscript.

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