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PROBABILISTIC DESIGN OF SUSTAINABLE REINFORCED CONCRETE INFRASTRUCTURE REPAIRS USING SIPMATH

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ABSTRACT

The design, construction, and operation of civil infrastructure that is more environmentally, socially, and economically responsible over its life cycle from extraction of raw materials to end of life is increasingly desirable worldwide. This paper presents a probabilistic framework for the design of civil infrastructure that achieves targeted improvements in quantitative sustainability indicators. The framework consists of two models: (i) probabilistic service life prediction models for determining the time to repair, and (ii) probabilistic life cycle assessment (LCA) models for measuring the impact of a repair. Specifically, this paper introduces a new mathematical approach, SIPmath, to simplify this design framework and potentially accelerate adoption by civil infrastructure designers. A reinforced concrete bridge repair in Norway is used as a case study to demonstrate SIPmath implementation. The case study shows that SIPmath allows designers to engage in sustainable design using probabilistic methods using the native, user-friendly Microsoft Excel® interface.

1 INTRODUCTION

The design, construction, and operation of civil infrastructure that is more environmentally, socially, and economically responsible over its full life cycle from extraction of raw materials to end of life is increasingly desirable worldwide. (Lepech 2018) These three design goals of improved environmental, social, and economic performance are commonly known as the "triple bottom line" of sustainability. As a critical set of systems that support quality of life and enable global development, while consuming vast amounts of material resources and energy, it is essential that civil infrastructure is designed according to these broad, long term design goals for the benefit of our planet and the current and future generations of humans, animals, and plants that will call it home.

While the goals of such sustainable design are well intended, the creation and execution of civil infrastructure designs that are socially, environmentally, and economically sustainable is not functionally possible for current practitioners. This inability is due to a lack of quantitative targets for a "sustainable" design, quantitative metrics for measurement and comparison of designs, and a probabilistic-based design approach that is translatable to engineering practices that manage uncertainty in infrastructure design, construction, and use. (Lepech 2018) Further, current approaches do not allow for simple, straightforward comparisons between systemic and aleatory uncertainty in design, and the costs associated with reducing such uncertainties. This is in contrast to probabilistic structural design approaches that are the hallmark of modern civil engineering design around the world (e.g., AISC-LRFD in the US, ACI-318 in the US, Eurocode 2 in Europe).

Along these lines, the design of sustainable rehabilitation of civil infrastructure proposed in this paper is based on the probabilistic framework for service life design proposed by the 2006 *fib* Model Code for

Service Life Design of Reinforced Concrete (*fib* 2006) and embodied in the *fib* 2010 Model Code (*fib* 2010). In Section 2, this paper provides an overview of the framework for probabilistic design of sustainable reinforced concrete infrastructure repairs. Section 3 presents the probabilistic design formulation and the novel application of SIPmath in native Excel® to enable simple, straightforward design comparisons by practitioners. Section 4 discusses the results of a simplified case study of a reinforced concrete bridge exposed to spray from roadway deicing salts. Section 5 provides conclusions.

2 FRAMEWORK FOR PROBABILISTIC DESIGN OF CIVIL INFRASTRUCTURE

Probabilistic design of sustainable civil infrastructure rehabilitations begins with measurement of the cumulative environmental, social, or economic impacts of a facility's repair and rehabilitation activities from initial construction up to the time of functional obsolescence. This is shown in Figure 1. (Lepech et al. 2013) Cumulative impact can be expressed as midpoint environmental indicators such as global warming potential (kg CO_2-equivalents), polluted water (L), solid waste (kg), or primary energy (MJ).

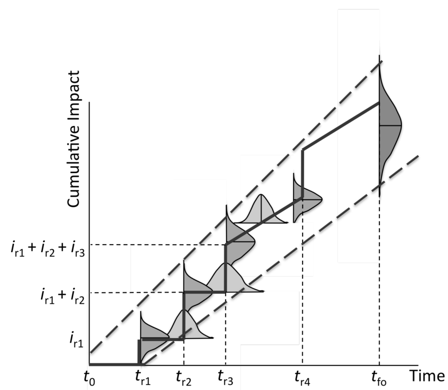

Figure 1: Probabilistic envelope of cumulative impacts of repairs and rehabilitations of civil infrastructure from initial construction (t_0) to functional obsolescence (t_{fo}) (Lepech et al. 2013).

As seen in Figure 1, the time at which any repair, *j*, is performed (t_{rj}) is probabilistically characterized based on reaching a service life limit state corresponding to an unacceptable reduction in materials quality or structural performance. These distributions are shown as horizontal Gaussian distributions for illustration. The probabilistic time between repairs ($t_{rj+1} - t_{rj}$) is based on the chosen repair strategy, the quality of the repair work, the variable nature of exposure and load conditions, the limit state, *etc.*

The cumulative impact of the repair timeline is the sum of all impacts associated with a facility's repair and rehabilitation from initial construction up to the time of functional obsolescence. Metrics of environmental impact are based on globally accepted environmental impact assessment midpoint indicator protocols (e.g., TRACI in the US, ReCiPe in Europe), which can include climate change, acidification, land use, energy, and toxicity indicators. As also seen in Figure 1, the impact associated with each repair or rehabilitation action is probabilistic in nature (shown as vertical Gaussian distributions for illustration). The impact associated with a given repair action, i_{rj}, can vary due to uncertainty in the repair construction processes used, uncertainty in the supply chain of repair materials, uncertainty in the effects on infrastructure users (e.g., how many automobiles are disrupted by the repair construction), *etc.*

Combining the probabilistic models for both repair timeline (t_{rj}) and amount of impact (i_{rj}), a probabilistic envelope can be constructed for the entire infrastructure service life from the time of initial construction (t_0) to the time of functional obsolescence (t_{fo}). Based on the boundaries of this larger envelope (shown as dashes in Figure 1), an aggregated probabilistic envelope of cumulative environmental, social, or economic impact at any time, t, for the repaired structure can be calculated.

Sustainable design targets are drawn from policy goals, which are derived from scientific, political, technological, or economic assessments of "sustainable development". For example, design targets could be adopted from the Intergovernmental Panel on Climate Change's proposed reductions in global greenhouse gas emissions. (IPCC 2013) A broader set of sustainable design targets are discussed in (Bakshi et al. 2015). With the goal of reducing impacts over time, an alternative (i.e., more sustainable) repair and rehabilitation scenario can be proposed.

The potential impact reduction using an alternative, more sustainable repair timeline versus a status quo repair timeline can be estimated probabilistically at any time in the future. For instance, to achieve a safe, stabilized atmospheric carbon-equivalent concentration of 500ppm to 550ppm, a 30% to 60% reduction in annual carbon-equivalent emissions is needed by Year 2050 (Year 2000 baseline) according to the UN Intergovernmental Panel on Climate Change. (IPCC 2013) Such reduction targets allow engineers to rationally design and probabilistically evaluate (through a probability of failure, $P_f(t)$), a cadre of infrastructure repair and rehabilitation timelines and technologies that meet proposed IPCC. Using this framework, engineers are incentivized to meet reduction targets at lowest economic cost, provided that the level of confidence that sustainability targets are met remains constant and acceptable. Tradeoffs between confidence levels (probabilities of failure) and cost can also be explicitly considered.

3 PROBABILISTIC SUSTAINABLE DESIGN FORMULATION IN EXCEL® USING SIPMATH

As seen from the orthogonal distributions in Figure 1, probabilistic sustainable design requires two distinct modeling components; (i) time-dependent modeling of material and structural deterioration, and (ii) cumulative environmental, social, and economic impacts of repair and rehabilitation activities. For a reinforced concrete structure undergoing a series of repairs over its lifetime, both of these components are described in the following sections. Also seen in Figure 1 is the interconnected nature of these two models, such that the design and completion of an individual repair activity heavily influences both the time until the next repair is needed along with the impacts associated with carrying out the repair activity.

3.1 Service Life Model

Service life models are used to quantify the performance of the structure over time. For demonstration purposes, a simple, probabilistic service life model for a reinforced concrete structure is adopted from the 2006 *fib* Model Code for Service Life Design of Reinforced Concrete. (*fib* 2006) This simple chloride-induced corrosion initiation (i.e., steel depassivation) model is convenient for demonstration of the SIPmath approach to performing sustainable design of civil infrastructure in Excel®. Based on Fick's Second Law, all that is needed are probabilistic quantifications of the corrosion initiation limit state and a model of chloride-induced reinforcement corrosion progress as a function of time.

As proposed in the 2006 *fib* Model Code for Service Life Design of Reinforced Concrete (*fib* 2006), the corrosion initiation limit state is defined by the chloride ion concentration at the location of the reinforcing steel reaching a critical concentration, as seen in (1).

$$\boldsymbol{C_{crit} = C\big((x,t) = (d,t)\big)} \tag{1}$$

where, C_{crit} is the critical chloride concentration in weight % of cement, $C(x,t)$ the chloride concentration in weight % of cement at time, t, at depth, x, from the concrete surface in meters, and d the concrete cover in meters.

The time dependent concentration of chlorides at depth, x, from the concrete surface is provided as (2) through (6).

$$\boldsymbol{C((x,t) = (d,t)) = C_0 + \big(C_{s,\Delta x} - C_0\big)\lambda} \tag{2}$$

$$\boldsymbol{\lambda = \left(1 - erf\left(\frac{d-\Delta x}{2\sqrt{D_{app,C}t}}\right)\right)} \tag{3}$$

$$\boldsymbol{D_{app,C} = k_e D_{RCM,0} k_t A(t)} \tag{4}$$

$$\boldsymbol{k_e = exp\left(b_e\left(\frac{1}{T_{ref}} - \frac{1}{T_{real}}\right)\right)} \tag{5}$$

$$\boldsymbol{A(t) = \left(\frac{t_0}{t}\right)^a} \tag{6}$$

where, C_0 is the initial chloride content of the concrete in weight % of cement, $C_{s,\Delta x}$ the chloride content at a depth Δx and a certain point in time in weight % of cement, *erf* the error function, Δx the depth of concrete convection zone in meters, $D_{app,C}$ the apparent chloride diffusion coefficient of the concrete in m^2/year, $D_{RMC,0}$ the chloride migration coefficient in m^2/year, k_e a dimensionless environmental transfer variable, b_e a regression variable in degrees K, T_{ref} a standard temperature in K, T_{real} the temperature of the reinforced concrete element or ambient air temperature in K, $A(t)$ a dimensionless aging variable expressed as a function of time, t, t_0 a reference time in years, and a a dimensionless aging exponent. The values or distributions in (2) through (6) are provided in Table 1.

Table 1: Service life modeling variables, distributions, and characteristic parameters.

Variable Name	**Distribution**	**Characteristic Parameters**	**Reference**
C_{crit}	Beta	α = 5.31, β = 18.58, min = 0.2, max = 2.0	(*fib* 2006)
$C_{s,\Delta x}$	Deterministic	2.325	(Vu 2000)
d	Normal	μ = Design Value, σ = 10mm	(*fib* 2006)
Δx	Beta	α = 1.9, β = 8.77, min = 0.06, max = 0.011	(*fib* 2006)
$D_{RCM,0}$	Normal	μ = Design Value, σ = 0.2μ	(*fib* 2006)
b_e	Normal	μ = 4800, σ = 700	(*fib* 2006)
T_{ref}	Deterministic	293.0	(*fib* 2006)
T_{real}	Normal	μ = Design Value, σ = Design Value	(*fib* 2006)
k_t	Deterministic	1.0	(*fib* 2006)
t_0	Deterministic	0.767	(*fib* 2006)
a	Beta	μ = Design Value, σ = Design Value	(*fib* 2006)

In order to compute the time to reach the critical chloride concentration at the reinforcement, the error function is modelled using an approximation by (Abramowitz and Stegun 1983), shown in (7) and (8).

$$\boldsymbol{erf(x) = 1 - \left(\sum_{i=1}^{5}\left(a_i \xi^i\right)\right) e^{-x^2}} \tag{7}$$

$$\boldsymbol{\xi = \frac{1}{1+px}} \tag{8}$$

where, p is equal to 0.3275911, a_1 is equal to 0.254829592, a_2 is equal to −0.284496736, a_3 is equal to 1.421413741, a_4 is equal to −1.453152027, and a_5 is equal to 1.061405429. (Abramowitz and Stegun 1983) report this numerical approximate to have a maximum error of 1.5 x 10^{-7} for positive values of x, which is the case in this circumstance since the values within the error function in (3) are limited to positive values between zero and one.

3.2 Environmental, Social, and Economic Impact Model

Life cycle assessment models are used to quantify the impacts (social, environmental, economic) of any system, product, process, or operation. LCAs are governed by ISO 14040 series standards. (ISO 2006a and ISO 2006b) Typically, all parts of a defined system are included within the LCA, including all life cycle phases (i.e., cradle to grave), and all inputs and output crossing the modeling boundary.

Following the ISO standards, after determining the scope and boundaries of the LCA, a life cycle inventory (LCI) is constructed to quantify all of the processes, materials, and flows that take place within and across the boundaries of the system. This life cycle inventory is then aggregated into a set of life cycle impact indicators through life cycle impact assessment (LCIA). In this project, these indicators include metrics such as global warming potential (CO_2-equivalents), acidification potential (H^+mol-equivalents), *etc*. As necessary, weighting among the various environmental indicators can be done based on predetermined weighting schemes among the disparate environmental impact indicators.

For the purposes of sustainable design of civil infrastructure a list of required inputs into the repair and rehabilitation actions is needed. Many of these inputs come from the construction estimation (bidding) documents and quantity estimates. Other information is taken from manufacturer's information (i.e., MSDS sheets), industry standards (i.e., EPA AP42), or discussions with material suppliers and contractors. Where possible, information on the type of distribution and parameters (e.g., normal distribution, mean, and standard distribution) associated with each of these values is requested.

3.3 Probabilistic Design of Repair and Rehabilitations Using SIPmath

As mentioned previously, current sustainable design approaches for civil infrastructure do not allow for simple, straightforward comparisons that consider systemic and aleatory uncertainty in engineering design, and the costs associated with reducing such uncertainties. In practice, most sustainable design of buildings and infrastructure has been reduced to a rubric of points, in which buildings are awarded silver, gold, or platinum status. Such approaches have effectively defined "sustainability" by the criteria used to recognize it (e.g., a gold rating or insignia). (Ehrenfeld 2007). As discussed by (Comello et al. 2012), these criteria are not formal logic definitions. Thus, the problem is the fundamental *ex post facto* nature of sustainability (i.e., today's developments can only be judged as sustainable from far in the future). Having sustainability framed in such long time frames, there is little incentive for designers to focus on sustainable practices due to, in part, the high levels of uncertainty regarding capital outlay and returns on investment. Thus, the introduction of a simple, straightforward approach to sustainable design of civil infrastructure that explicitly considers uncertainty is a central component of this paper.

The requirements of a simple, straightforward approach are met in native Excel® by using SIPmath. SIPmath probabilistic modeling performs computations using Stochastic Information Packets (SIPs), in which uncertainty is modeled in Excel® as an array of possible outcomes. (Savage and Thibault 2015) Using SIPmath, uncertainties are represented as myriad possible outcomes within an array (SIPs). Due to their additive nature, SIPs may be operated on element by element with any algebraic operator through vectorization. Thus, if x and y are random variables from a joint distribution where SIP(x) and SIP(y) are arrays of realizations that preserve statistical dependence, the addition of SIPs is performed element by element over the arrays, preserving the additive relationship, shown in (9).

$$\boldsymbol{SIP}(\boldsymbol{x}+\boldsymbol{y}) = \boldsymbol{SIP}(\boldsymbol{x}) + \boldsymbol{SIP}(\boldsymbol{y}) \tag{9}$$

This additive nature holds as the mathematical operators increase in complexity, as shown in (10) and (11), since the mathematical operations are taken element by element in the arrays.

$$\boldsymbol{SIP}(\boldsymbol{x}\cdot\boldsymbol{y}) = \boldsymbol{SIP}(\boldsymbol{x}) \cdot \boldsymbol{SIP}(\boldsymbol{y}) \tag{10}$$

$$\boldsymbol{SIP}\big(\boldsymbol{x}\cdot\boldsymbol{cos}(\boldsymbol{y})\big) = \boldsymbol{SIP}(\boldsymbol{x}) \cdot \boldsymbol{cos}\big(\boldsymbol{SIP}(\boldsymbol{y})\big) \tag{11}$$

At its core, SIPmath is simply Monte Carlo simulation, except that the variables x and y are generated in advance, and stored in arrays, as are the output trials. This preprocessing enables rapid probabilistic analysis of many uncertain variables simultaneously in native Excel®. Since the outcomes are stored as output trials, SIPmath also allows for auditing of design practices and decision-making, which is an essential component of the peer review design process used for the design of major civil infrastructures.

4 CASE STUDY

4.1 OFU Gimsøystraumen Bridge

To demonstrate the design framework, a case study was carried out based on trial repair activities performed on the OFU Gimsøystraumen Bridge in Norway from 1993 to 1995. A summary of the OFU-Gimsøystraumen Bridge Repair Project can be found in (Blankvoll 1998). While the case study repair timeline proposed was never performed, the design, planning, and execution of the trial repair serves as a valuable dataset for case study. A more detailed discussion can also be found in (Lepech et al. 2014)

The repair was performed from 1993 to 1995 and comprised the repair of columns and superstructure between Piers 1 and 3 of the bridge. The trial repair modeled for this case study was a mechanical repair that was comprised of water hydrodemolition of existing, chloride-infiltrated cover, and dry shotcreting of new concrete cover that measured 0.04m thick. The repairs are assumed to take place offset from the active traffic lane, with chlorides coming from deicing-salt spray and splash. The traffic over the bridge was approximately 3000 vehicles per day, however no traffic was interrupted during the completion of the trial repair due to the working location outside of active traffic lanes. The ambient air temperature at the site is assumed to be normally distributed with a mean of 279.9°K and standard deviation of 10.93°K.

The case study in this paper applies SIPmath to sustainable design of two repair types and timelines; (i) a 0.04m thick cover replacement, and (ii) an 0.08m thick cover replacement. For each of repair type, a probabilistic service life timeline prediction is constructed (following Section 3.1), along with a probabilistic life cycle inventory of the repair work activities (following Section 3.2).

4.2 Service Life Model of OFU Gimsøystraumen Bridge Repairs

Using the service life model discussed in Section 3.1, a probabilistic chloride-induced corrosion initiation model was constructed in Excel® using SIPmath. In addition to the variables, distributions, and parameters shown in Table 1, a number of design-specific variables, distributions, and parameters are given in Table 2. For this case study, ordinary Portland cement concrete with a water-to-cement ratio of 0.45 was assumed. No supplementary cementitious materials (i.e., fly ash) were used in the concrete.

Table 2: Service life modeling parameters specific to the OFU Gimsøystraumen Bridge repair case study.

Variable Name	Distribution	Characteristic Parameters	Reference
d	Normal	(Repair 1) $\mu = 0.04$, $\sigma = 10$mm; (Repair 2) $\mu = 0.08$, $\sigma = 10$mm	
$D_{RCM,0}$	Normal	$\mu = 3.14 \times 10^{-4}$, $\sigma = 6.31 \times 10^{-5}$	(*fib* 2006)
T_{real}	Normal	$\mu = 280$, $\sigma = 11.0$	
a	Beta	$\alpha = 4.08$, $\beta = 9.51$, min = 0.0, max = 1.0	(*fib* 2006)

The sequence of future repairs was modeled as a Markovian chain of independent, recurring, identical deterioration and repair processes according to (12). The construction duration of any one repair activity is considered to be irrelevant when considered within the decades-long service life of the bridge.

$$\boldsymbol{P(t_{n+1} = x | t_{n=y}) = P(t_n = x | t_{n-1=y})} \tag{12}$$

where, P is the probability that the time to the next repair will take time, t, (t_{n+1}) the time from most recent repair event, n, to next repair event, ($n+1$), t_n the time from the second most recent repair event, ($n-1$), to the most recent repair event, n, (t_{n-1}) the time from the third most recent repair event, ($n-2$), to the second most recent repair event, (*n-1*), and *x* and *y* are random probabilities. Thus, the time of any future repair event (t_{rj} in Figure 1) is the sum of the times to repair of all previous repair events, as shown in (13).

$$\boldsymbol{t_{rj} = \sum_{n=1}^{j}\big(t_n(C(x=d)=C_{crit})\big)} \tag{13}$$

where, t_{rj} is the time at which any repair, *j*, is performed, and $t_n(C(x=d)=C_{crit})$ the time elapsing between the performance of repair action, *n*, and a critical concentration of chlorides reaching the location of the reinforcing steel a distance, *d*, from the concrete surface.

4.3 Environmental, Social, and Economic Impact Model of OFU Gimsøystraumen Bridge Repairs

To determine the life cycle impacts of repairs, a life cycle inventory of the repair materials, processes, and procedures was constructed. The main sources for this data were (Kompen et al. 1997), primary data from contractors, product marketing materials, personal safety and hygiene sheets (MSDS), and commercial life cycle inventory datasets. Once again, a more detailed account can be found in (Lepech et al. 2014) The mechanical repair comprised five steps; (i) hydrodemolition of deteriorated concrete cover, (ii) shotcreting of replacement concrete, (iii) application of a sprayed curing membrane, (iv) sandblasting of the surface, and (v) surface treatment with an elastic mortar. For each of these steps the commercial products used, the equipment needed, and the transportation of materials to the site were catalogued. The total environmental impact is the sum of impacts from all repair steps, as shown in (14).

$$\boldsymbol{i_{rj} = \sum_{k=1}^{5} i_k} \tag{14}$$

where, i_{rj} is the impact (social, environmental, or economic) of performing repair, *j*, and i_k is the impact of performing one of the five steps, *k*, of the mechanical repair. For demonstration purposes, global warming potential (kg CO_2-equivalents) will be used as a proxy for overall environmental impact.

The impact due to hydrodemolition, i_1, is computed as the sum total of impacts associated with water use, water for washdown purposes, waste disposal of the concrete, and impacts associated with the hydrodemolition equipment and shown in (15). The hydrodemolition equipment used includes an air compressor, a hydrodemoltion machine, and a front-end loader. Productivity rates and equipment needs were determined from RS Means Construction Cost Data (RS Means 2008).

$$\begin{aligned}\boldsymbol{i_1} &= \boldsymbol{i_{H_2O} r_{H_2O} d a_{HYDRO} + i_{H_2O} r_{WASH} + i_{LANDFILL} d a_{HYDRO} \rho_{CONC}} \\ &\quad \boldsymbol{+ (i_{AIR} r_{AIR} \gamma_1 + i_{HYDRO} e_{HYDRO} \gamma_2 + i_{LOADER} r_{LOADER}) r_{HYDRO}}\end{aligned} \tag{15}$$

where, i_1 is the impact of hydrodemolition, i_{H2O} the impact of producing water in kg CO_2-eq per kg, r_{H2O} the rate of water use for hydrodemolition in kg per m^3 of concrete removed, *d* the cover thickness in meters, a_{HYDRO} the area being hydrodemolished in m^2, r_{WASH} the rate of water use for washdown in kg per m^2 of hydrodemolition, $i_{LANDFILL}$ the impact of landfilling the waste per kg, ρ_{CONC} the density of concrete in kg/m^3, i_{AIR} the impact of operating an air compressor per m^2 of hydrodemolition, r_{AIR} the energy consumption of an air compressor in horsepower, γ_1 is a unit conversion factor, i_{HYDRO} the impact of operating a hydrodemolition machine per m^2 of hydrodemolition, e_{HYDRO} the energy consumption of a hydrodemolition machine in kW, γ_2 a unit conversion factor, i_{LOADER} the impact of operating a loader per m^2 of hydrodemolition, r_{LOADER} the productivity of a loader in m^3/hr, and r_{HYDRO} the productivity of a hydrodemolition crew in hours per m^2 of hydrodemolition. Distributions and parameters for these variables are provided in Table 3.

Table 3: Hydrodemolition environmental impact modeling variables, distributions, and parameters.

Variable Name	Distribution	Characteristic Parameters	Reference
i_{H2O}	Deterministic	0.000998	(Lepech et al. 2014)
r_{H2O}	Deterministic	100024	(Lepech et al. 2014)
a_{HYDRO}	Deterministic	Design Value	(Lepech et al. 2014)
r_{WASH}	Deterministic	60.0	(Lepech et al. 2014)
$i_{LANDFILL}$	Deterministic	0.000546	(Lepech et al. 2014)
ρ_{CONC}	Normal	$\mu = 2250$, $\sigma = 52$	(Lepech et al. 2014)
i_{AIR}	Deterministic	0.0885	(Lepech et al. 2014)
r_{AIR}	Uniform	min = 48, max = 111	(Lepech et al. 2014)
γ_1	Deterministic	2.68 x 10^{-6}	(Lepech et al. 2014)
i_{HYDRO}	Deterministic	0.0885	(Lepech et al. 2014)
e_{HYDRO}	Uniform	min = 250, max = 750	(Lepech et al. 2014)
γ_2	Deterministic	3.60 x 10^{-6}	(Lepech et al. 2014)
i_{LOADER}	Deterministic	0.546	(Lepech et al. 2014)
r_{LOADER}	Deterministic	150	(Lepech et al. 2014)
r_{HYDRO}	Uniform	min = 0.24, max = 0.37	(Lepech et al. 2014)

The impact from the shotcreting step, i_2, is computed as the sum total of impacts associated with production of the shotcrete, impacts associated with equipment on site, and impacts from transportation of the shotcrete material from the producer to the construction site, as shown in (16). The shotcrete equipment used includes an air compressor, a shotcrete rig, and a concrete pump. Productivity rates and equipment needs were determined from RS Means Construction Cost Data (RS Means 2008). Material proportions and species were determined from product information sheets provided by the manufacturer or environmental health and safety documentation.

$$\begin{aligned} \boldsymbol{i_2} &= \left(\boldsymbol{i_C p_C + i_{H_2O} p_{H_2O} + i_S p_S}\right)\boldsymbol{d a_{HYDRO}(1 + r)} \\ &+\boldsymbol{i_{LANDFILL} d a_{HYDRO}}\left(\boldsymbol{p_C + p_{H_2O} + p_S}\right)\boldsymbol{r} \\ &+\left(\boldsymbol{i_{AIR} r_{AIR} \gamma_1 + i_{PUMP} e_{PUMP} \gamma_2 + i_{RIG} e_{RIG}}\right)\boldsymbol{r_{SHOT}} \\ &+\boldsymbol{i_T d a_{HYDRO}}\left(\boldsymbol{p_C + p_{H_2O} + p_S}\right)\boldsymbol{(1 + r) d_{SHOT} \gamma_3} \end{aligned} \tag{16}$$

where, i_2 is the impact of the shotcrete step, i_C the impact of producing cement in kg CO_2-eq per kg, p_C the proportion of cement in shotcrete in kg of cement per m^3 of shotcrete, p_{H2O} the proportion of water in shotcrete in kg of water per m^3 of shotcrete, i_S the impact of producing sand and gravel in kg CO_2-eq per kg, p_S is the proportion of sand or gravel in shotcrete in kg of sand or gravel per m^3 of shotcrete, r the portion of shotcrete wasted in rebound, i_{PUMP} the impact of operating shotcrete pump per m^2 of hydrodemolition performed, e_{PUMP} the energy consumption of a shotcrete pump in kW, i_{RIG} the impact of shotcrete rig truck per m^2 of hydrodemolition performed, e_{RIG} the fuel consumption of a shotcrete rig truck in L of diesel fuel per hour, r_{SHOT} the productivity of a shotcrete crew in hours per m^2 of shotcreting repair performed, i_T the impact of truck transportation in tonne-km, d_{SHOT} the distance shotcrete materials were shipped in km, and γ_3 a unit conversion factor. Distributions and characteristic parameters for these variables are provided in Table 4.

Table 4: Shotcreting environmental impact modeling variables, distributions, and parameters.

Variable Name	Distribution	Characteristic Parameters	Reference
i_C	Deterministic	0.826	(Lepech et al. 2014)
p_C	Uniform	min = 224.3, max = 672.8	(Lepech et al. 2014)
p_{H2O}	Uniform	$0.5p_C$	(Lepech et al. 2014)
i_S	Deterministic	0.00859	(Lepech et al. 2014)
p_S	Uniform	$2230 - p_C - p_{H2O}$	(Lepech et al. 2014)
r	Uniform	min = 0.02, max = 0.03	(Lepech et al. 2014)
i_{PUMP}	Deterministic	0.0885	(Lepech et al. 2014)
e_{PUMP}	Deterministic	30	(Lepech et al. 2014)
i_{RIG}	Deterministic	3.08	(Lepech et al. 2014)
e_{RIG}	Deterministic	3.785	(Lepech et al. 2014)
r_{SHOT}	Deterministic	0.431	(Lepech et al. 2014)
i_T	Deterministic	0.217	(Lepech et al. 2014)
d_{SHOT}	Deterministic	1400	(Lepech et al. 2014)
γ_3	Deterministic	0.001	(Lepech et al. 2014)

The impact from application of an impermeable membrane, i_3, sums impacts associated with production of the membrane material and impacts from transportation of materials to the construction site (17). The membrane is applied with a hand sprayer in two applications. Material proportions were determined from manufacturer product information or environmental health and safety documentation.

$$\boldsymbol{i_3 = \left(i_M p_M + i_N p_N + i_T(p_M + p_N)\right) n_{APP} r_{APP} (1 + d_{MEM}\gamma_3)} \tag{17}$$

where, i_3 is the impact of the membrane application, i_M the impact of producing methacrylate in kg CO_2-eq per kg, p_M the proportion of methacrylate in the membrane in kg per L of material, i_N the impact of producing naphtha in kg CO_2-eq per kg, p_N the naphtha proportion of the membrane in kg per L of material, n_{APP} the number of applications, r_{APP} the rate of membrane application in L per m^2 of repair, and d_{MEM} the distance that materials were shipped in km. Distributions and parameters are in Table 5.

Table 5: Membrane application environmental impact modeling variables, distributions, and parameters.

Variable Name	Distribution	Characteristic Parameters	Reference
i_M	Deterministic	6.03	(Lepech et al. 2014)
p_M	Uniform	min = 0.36, max = 0.9	(Lepech et al. 2014)
i_N	Deterministic	0.651	(Lepech et al. 2014)
p_N	Uniform	$1 - p_M$	(Lepech et al. 2014)
n_{APP}	Deterministic	2	(Lepech et al. 2014)
r_{APP}	Deterministic	0.14	(Lepech et al. 2014)
d_{MEM}	Deterministic	1400	(Lepech et al. 2014)

The impact from sandblasting, i_4, is the sum total of impacts associated with production of the sandblasting medium, operation of an air compressor, material transportation to the construction site, and impacts from landfilling of the waste medium (18). The sand blasting medium, Star-Grit, is comprised of recycled copper slag. Material proportions were determined from manufacturer information.

$$\boldsymbol{\begin{aligned} i_4 = (i_{SLAG} p_{SLAG} + i_S p_{S-SLAG}) w_{MED} + i_{AIR} r_{AIR} \gamma_1 r_S \\ + i_{SHIP} w_{MED} d_{SAND} \gamma_3 + i_{WASTE} w_{MED} \end{aligned}} \tag{18}$$

where, i_4 is the sandblasting impact, i_{SLAG} the impact of producing the slag portion of the sandblasting medium in kg CO_2-eq per kg, p_{SLAG} the slag proportion of the medium in kg of slag per kg, $p_{S\text{-}SLAG}$ the proportion of sand in the medium in kg of sand per kg, w_{MED} the mass of medium in kg consumed per m^2 of sandblasting, r_S the crew productivity in hours per m^2, i_{SHIP} the impact of ship transportation in tonne-km, and d_{SAND} the shipping distance in km. Distributions and parameters are in Table 6.

Table 6: Sandblasting environmental impact modeling variables, distributions, and parameters.

Variable Name	**Distribution**	**Characteristic Parameters**	**Reference**
i_{SLAG}	Deterministic	0.0	(Lepech et al. 2014)
p_{SLAG}	Uniform	min = 0.9, max = 1.0	(Lepech et al. 2014)
$p_{S\text{-}SLAG}$	Uniform	1 - p_{SLAG}	(Lepech et al. 2014)
w_{MED}	Uniform	min = 0.82, max = 1.18	(Lepech et al. 2014)
r_S	Uniform	min = 0.078, max = 0.228	(Lepech et al. 2014)
i_{SHIP}	Deterministic	0.00844	(Lepech et al. 2014)
d_{SAND}	Deterministic	2000	(Lepech et al. 2014)

The impact from surface treatment of the repair, i_5, is computed as the sum total of impacts associated with production of the surface treatment materials and impacts from transportation of the surface treatment materials to the construction site, as shown in (19). No mechanical equipment is used in the application of the surface treatment. Material proportions and species were determined from product information sheets provided by the manufacturer or environmental health and safety documentation.

$$\boldsymbol{i_5 = i_C p_{C-SURF} + i_S p_{S-SURF} + i_L p_{L-SURF} + i_T w_{SURF} d_{SURF} \gamma_3} \tag{19}$$

where, i_5 is the impact of the surface treatment, $p_{C\text{-}SURF}$ the proportion of cement used in the surface treatment mortar in kg per m^2 of surface treatment, $p_{S\text{-}SURF}$ the proportion of sand used in the surface treatment mortar in kg per m^2, i_L the impact of producing the latex portion of the surface treatment mortar in kg CO_2-eq per kg of latex, $p_{L\text{-}SURF}$ the proportion of latex used in the surface treatment mortar in kg per m^2, w_{SURF} the mass of surface treatment mortar in kg consumed per m^2, and d_{SURF} the distance that materials were shipped in km. Distributions and characteristic parameters are provided in Table 7.

Table 7: Surface treatment environmental impact modeling variables, distributions, and parameters.

Variable Name	**Distribution**	**Characteristic Parameters**	**Reference**
$p_{C\text{-}SURF}$	Uniform	min = 0.21, max = 0.63	(Lepech et al. 2014)
$p_{S\text{-}SURF}$	Uniform	3.1 - $p_{C\text{-}SURF}$ - $p_{L\text{-}SURF}$	(Lepech et al. 2014)
i_L	Deterministic	2.52	(Lepech et al. 2014)
$p_{L\text{-}SURF}$	Deterministic	0.74	(Lepech et al. 2014)
w_{SURF}	Deterministic	min = 3.1	(Lepech et al. 2014)
d_{SURF}	Deterministic	1400	(Lepech et al. 2014)

4.4 Analysis and Sustainability Design of Repair Scenarios using SIPmath in Excel®

Using SIPmath in Microsoft Excel®, modeling of cumulative impact envelopes, shown schematically in Figure 1, was done using a total of four interdependent workbooks. The model is interactive, such that the user can change the repair thickness, d, along with the mean and standard deviation of the ambient temperature, T_{real}. For illustration the cumulative impact was predicted for an 80-year analysis period for each of the repairs considered (0.04m and 0.08m) is shown in Figures 2(a) and 2(b), respectively.

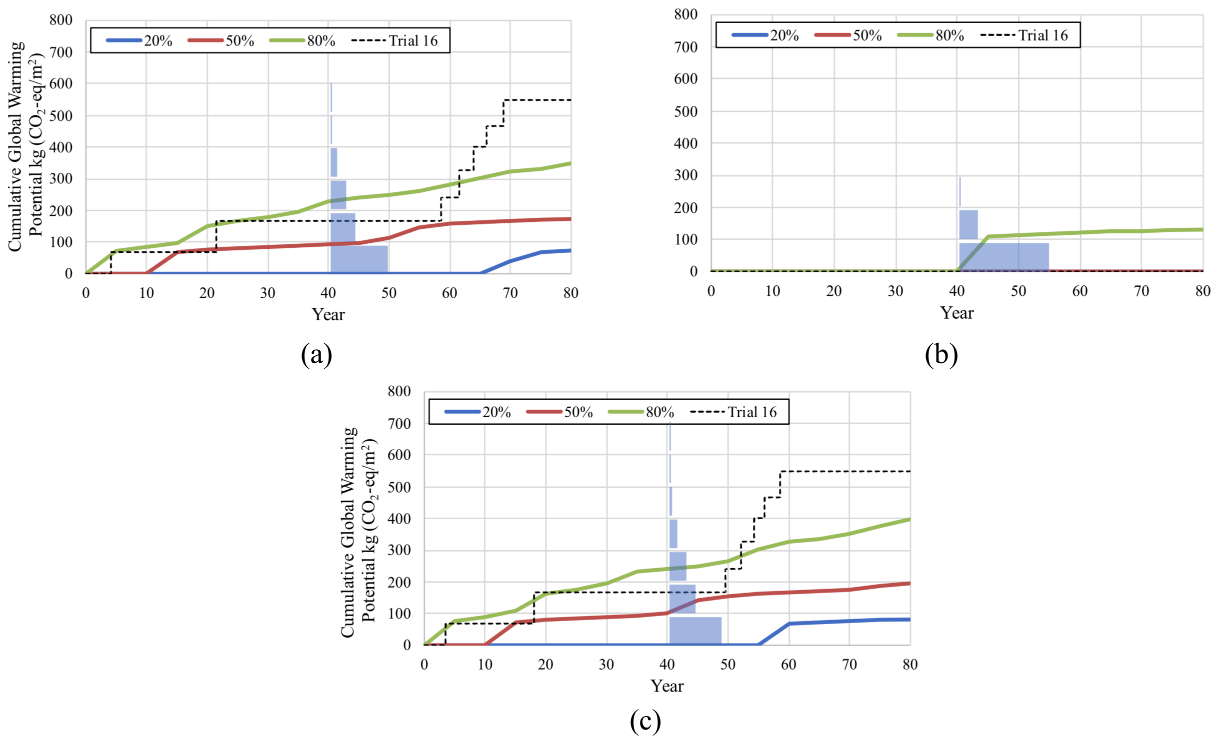

Figure 2: Cumulative global warming potential envelopes (kg CO_2-eq/m^2) for (a) 0.04m, (b) 0.08m repair, and (c) 0.04m repair + 2°C timelines. For all three, the 20th, 50th, and 80th percentiles are plotted, as is one example timeline (Trial 16). The distributions of cumulative GWP are shown schematically for Year 40.

As seen in Figure 2, increasing cover thickness from 0.04m to 0.08m effectively reduced total carbon emissions over an 80-year analysis period. Also, by the end of 80 years there is enough difference in the CO_2-eq emissions of the 0.04m and 0.08m timelines to give confidence that the 0.08m repair is the more sustainable choice. Taking the model further, the effect of climate change can be explored. Figure 2(c) shows the cumulative envelope for a 0.04m repair timeline under a temperature rise of 2°C. (IPCC 2013)

While slight, there is a noticeable increase in the cumulative global warming potential for timelines exposed to higher temperatures. Given that these results are only for one square meter of repairs over an 80-year analysis period, the results become more concerning when considering the myriad concrete repairs performed annually worldwide. Moreover, the vicious cycle of carbon emissions leading to temperature rise, leading to faster deterioration of concrete infrastructure, leading to more repairs, leading to increased carbon emissions becomes clearer to decision-makers. This clarity is motivation for the development of easy-to-use probabilistic modeling and design tools using SIPmath modeling.

5 CONCLUSIONS

This paper presented a probabilistic framework for the design of civil infrastructure that achieves targeted improvements in quantitative sustainability indicators. The framework consists of two types of models; (i) probabilistic service life prediction models, and (ii) probabilistic life cycle assessment (LCA) models. Specifically, this paper introduced a new mathematical approach, SIPmath, to simplify sustainability-focused design and potentially accelerate its adoption by infrastructure designers. A reinforced concrete bridge repair in Norway was presented as a case study to demonstrate SIPmath implementation.

Ultimately, the case study showed that SIPmath tools can provide designers and engineers an engaging tool for sustainability-focused probabilistic design of reinforced concrete infrastructure. The analysis showed that a 0.08m concrete repair was preferable to a 0.04m concrete repair over the 80-year analysis period of the OFU Gimsøystraumen Bridge. Additionally, the effect of a 2°C increase in annual average temperature associated with global climate change had a noticeable effect on the cumulative carbon emission profile of the case study bridge. Future work will continue to expand the use of SIPmath to compute the time dependent probabilities of failure of meeting environmental targets.

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