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A life-cycle assessment framework for pavement management considering uncertainties

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ABSTRACT: Life cycle assessment (LCA) is a methodology widely endorsed by the pavement community and increasingly adopted by transportation agencies worldwide to account for the environmental impacts of pavements throughout their entire life cycle. LCA studies in this context are prone to the effects of uncertainties due to (1) the long analysis periods that stretch across numerous maintenance and rehabilitation (M&R) cycles, (2) the need of different types and sources of data and additional models and (3) multiple methodological decisions to be made by the analyst. Nevertheless, LCA studies are often done deterministically and omit important phases and phenomena from the systems boundaries, thereby reducing the reliability and representativity of the results. To overcome this challenge and to foster the integration of LCA models with existing pavement management systems, this paper presents the development and application of a LCA framework that evaluates the environmental performance of pavement M&R treatments. Further, it incorporates the effects of pavement-vehicle interaction into the analysis and accounts for multiple types of uncertainties, namely those associated with the value of parameters, methodological choices and data quality. Probability distributions and value scenarios are used to characterize the uncertainties which are propagated into the results using Latin hypercube sampling and scenario analysis. A sensitivity analysis using tree-ensemble methods is adopted to unveil the most influential parameters on the variance of the outputs. The outcomes of this research work aim to advance the applicability of LCA in the context of pavement management, and to improve the understanding of the effects of uncertainties in the outcomes of the analysis.

1 INTRODUCTION

Road pavements are long-lived infrastructures that undergo periodic maintenance and rehabilitation (M&R) treatments over their lifetime. The application of such treatments ensures that pavement condition remains above desirable levels, but it also results in significant cumulative environmental impacts due to the vast consumption of natural resources and energy it entails. In light of the rising environmental awareness, assessing the environmental impacts of road pavements is an important step towards the achievement of sustainability goals.

Life cycle assessment (LCA) is an approach that evaluates the environmental impacts of road pavements over the course of their service life that has gained significant recognition in the field of pavement management (PM) and has become instrumental in the context of sustainability transition (Miliutenko *et al.*, 2014; Rangelov *et al.*, 2020; Santero *et al.*, 2011; Santos *et al.*, 2015). However, the validity of LCA in this setting is often called into question, as most pavement LCA studies tend to exclude important phases from the system boundaries of the analysis, particularly the use phase (Xu *et al.*, 2019), and ignore the effects of uncertainty on the results.

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LCA offers the option to calculate the impacts of pavement materials production, construction, use, M&R, and end-of-life (EOL) (Santero *et al.*, 2011). Conventionally, the focus of the assessment has been placed in the production, construction and EOL phases (Xu *et al.*, 2019). However, as the environmental impacts of the use phase may represent a large share of total life cycle impacts (Harvey *et al.*, 2016; Santos *et al.*, 2022), recent LCA studies have begun to account for the effects of pavement-vehicle interaction (PVI), a use phase mechanism, in their assessments (Akbarian *et al.*, 2012; Gregory *et al.*, 2016; Noshadravan *et al.*, 2013; Santos *et al.*, 2022). PVI is the relationship between pavement characteristics and vehicle fuel efficiency, determined by pavement rolling resistance (RR). As RR increases, so do the fuel consumption and the emissions generated by the vehicles moving across the road (Bryce et al., 2014; Van Dam et al., 2015). Although in a comprehensive analysis it is essential to take into account every phase of the pavements' life cycle to ensure representativity and accuracy, the absence of the use phase is not the only omission often found in multiple pavement LCA studies.

Uncertainty is unavoidable in LCA studies, and despite the fact that it directly affects the reliability of the results, conventional LCA analyses often consider single input values. The need for the consideration of uncertainties in LCA has been recognized in the past (Huijbregts, 1998; Santero *et al.*, 2011), but limited attention has been given to developing and including uncertainty analysis approaches in LCA studies (Lo Piano and Benini, 2022), let alone in the pavement domain.

The first step of a un uncertainty analysis in LCA consists of identifying and selecting the main types and sources of uncertainty (Igos *et al.*, 2019). This includes distinguishing between parameter and scenario uncertainty. Parameter uncertainty is primarily caused by inaccuracies in input data used to model processes and flows caused by data quality and variability. LCA studies in the pavement domain place attention on several specific sources of parameter uncertainty related to the different pavement life cycle phases (Azarijafari *et al.*, 2018; Gregory *et al.*, 2016; Noshadravan *et al.*, 2013; Santos *et al.*, 2022), including PVI and the models used to predict the pavement condition over time (Gregory *et al.*, 2016; Noshadravan *et al.*, 2013; Santos *et al.*, 2022; Ziyadi *et al.*, 2017). Among other sources, scenario uncertainty arises from methodological and normative choices made during the goal and scope definition, such as LCA software and LCI database selection (Santos *et al.*, 2017), system boundary choices (Gregory *et al.*, 2016), allocation methods (Azarijafari *et al.*, 2018), etc.

After identifying sources and types of uncertainty, the next step is to characterize them. Characterization can be done qualitatively or quantitatively. In qualitative characterizations, it is common practice to estimate data quality levels and to construct alternative scenarios based on different methodological choices (Igos *et al.*, 2019). The pedigree matrix approach implemented in the ecoinvent database (Weidema *et al.*, 2013) has been employed in the pavement LCA field to account for the uncertainty due to data quality, rendering its further quantitative characterization possible (Azarijafari *et al.*, 2018; Gregory *et al.*, 2016; Noshadravan *et al.*, 2013). Quantitatively, uncertainties can be characterized by defining minimum and maximum parameter values and/or probability density functions (PDFs) (Igos *et al.*, 2019). Data variability can be represented with PDFs when the sample size is large (Yu *et al.*, 2018), or by minimum and maximum values for smaller sample sizes (Gregory *et al.*, 2016). When only single values are available, predetermined uncertainty values retrieved from the ecoinvent database can be used (Azarijafari *et al.*, 2018; Gregory *et al.*, 2016; Noshadravan *et al.*, 2013). In turn, scenarios can be represented by discrete choices with equal likelihood or with alternative value scenarios (e.g., minimum and maximum values) (Azarijafari *et al.*, 2018; Gregory *et al.*, 2016).

Once uncertainties have been characterized, they are propagated to the results. Two common methods used in pavement LCA literature are Monte Carlo sampling (MCS) and scenario analysis (Azarijafari *et al.*, 2018; Gregory *et al.*, 2016; Noshadravan *et al.*, 2013; Santos *et al.*, 2022; Yu *et al.*, 2018). MCS is a commonly used method to propagate parameter uncertainties (Igos *et al.*, 2019). However, it requires large sample sizes and can be computationally expensive. To reduce the computational time, Latin hypercube sampling (LHS) can be used. It is an efficient modification of MCS that divides the input distribution into equal intervals from which a sample point is selected randomly (Groen *et al.*, 2014; Igos *et al.*, 2019). It guarantees that all intervals are sampled equally, and that no area is over- or under-sampled. Therefore, it is particularly useful for contexts where the sample size must be kept as small as possible. Scenario analysis entails the single or simultaneous variation of parameters, methodological choices and model formulations to analyze uncertainties in LCA (Igos *et al.*, 2019). Sampling and scenario analysis can be used together to combine parameter and scenario uncertainties (Azarijafari *et al.*, 2018; Gregory *et al.*, 2016).

Moreover, a comprehensive uncertainty analysis in LCA should include a sensitivity analysis to investigate how changes in parameters and methodological choices affect the results (Harvey *et al.*, 2016) and to identify which elements have the largest contributions to the overall uncertainty (Igos *et al.*, 2019). In the pavement field, one-at-a-time analyses (Godoi Bizarro *et al.*, 2020) and Spearman's rank correlation coefficients (Gregory *et al.*, 2016) have been used to identify the most influential parameters and scenarios. In other fields, the calculations of Sobol indices (Igos *et al.*, 2019; Jaxa-Rozen *et al.*, 2021a), a well-known global sensitivity analysis (GSA) technique, has been adopted to quantify the relationship and importance of each input in the variance of the LCA outputs. However, this method comes at a high computational cost. In turn, Extra Trees is a computational efficient method that can handle large number of parameters and produce reliable results at smaller sample sizes, while offering results comparable to those of Sobol indices (Jaxa-Rozen and Kwakkel, 2018). In LCA, Extra Trees has been used as a preliminary screening step to identify the most influential parameters on the uncertainty (Jaxa-Rozen *et al.*, 2021a), but to the authors' best knowledge it has never been applied in the pavement LCA field.

In view of the considerations and limitations mentioned above, this study aims to further expand the development and applicability of LCA in the context of sustainable pavement management by creating a framework tailored to road pavement M&R that accounts for the effects of PVI and includes a comprehensive uncertainty analysis methodology.

2 METHODS

2.1 *LCA framework*

The proposed LCA framework described in this paper focuses on the LCA of individual pavement M&R cycles that involve the application of asphalt overlays, although it can be expanded to include any other type of M&R treatments. LCA studies in the context of M&R often cover long analysis periods spanning multiple M&R cycles. In the current setting the analysis period is constrained to the time between the application of a treatment and the subsequent need for a new one. In addition to the analysis period, the definition of the functional unit considers the characteristics of the pavement system being treated, including its structure (surface, binder, and/or base layers and subgrade), geometrical and functional characteristics, materials and the traffic it is expected to carry (Harvey *et al.*, 2016).

Moreover, the LCA framework is consistent with Dutch reference documents, specifically the asphalt product category rules (NL-PCR) (Van der Kruk *et al.*, 2022) and the Determination Method (Nationale Milieudatabase, 2020). The system boundaries for the analysis encompass all relevant life cycle processes and flows, including the production (material extraction, acquisition, transportation, and processing into asphalt mixtures), construction (on-site paving activities and equipment use), use (processes that impact the environment during the service life, with an emphasis on PVI) and end-of-life (EOL) phases (i.e. removal, recycling and transportation of waste materials) as outlined by Santero et al., (2011).

2.2 *Uncertainty analysis*

The uncertainty analysis starts with the identification of the different foreground-related uncertain parameters and methodological choices that potentially can influence the environmental impact calculations. Although accounting for uncertainty related to the background is to some extent feasible and would result in a more robust analysis, its actual realization would imply an extreme increase of the number of uncertain parameters and the level of complexity the analysis.

Data variability can be represented with PDFs derived from empirical data when available, or with the predefined values provided by the ecoinvent method in the absence of empirical data

(Weidema *et al.*, 2013). These values are then aggregated with data quality uncertainty according to the criteria established by the ecoinvent method, with data quality being described using log-normal distributions. The procedure provided by Muller et al., (2016) is adopted to facilitate the numerical integration with data quality uncertainty values when data variability is represented using distributions other than log-normal. Scenarios are developed based on different value options, such as different machinery production rates, recycled asphalt pavement (RAP) content in the composition of the mixture, and the type of bitumen added.

In the proposed LCA framework the propagation of uncertainties to the results involves the application of a combination of LHS and scenario analysis. LHS is employed to reduce computational time in the evaluation of parameter uncertainty. Scenario analysis, in turn, is used to evaluate the effect of changing scenarios. According to Jaxa-Rozen et al., (2021), 12,000 simulations are sufficient for the LHS analysis when the sensitivity analysis method is adequate for a relatively small number of samples. As such, the Extra Trees method is adopted to identify the most influential parameters in the uncertainty of the outcomes for different scenarios following the configuration recommended by Jaxa-Rozen and Kwakkel, (2018). It is important to note that LHS should be performed for each scenario considered in the analysis, allowing for its subsequent sensitivity analysis. Figure 1 summarizes the uncertainty methodology proposed in the framework.

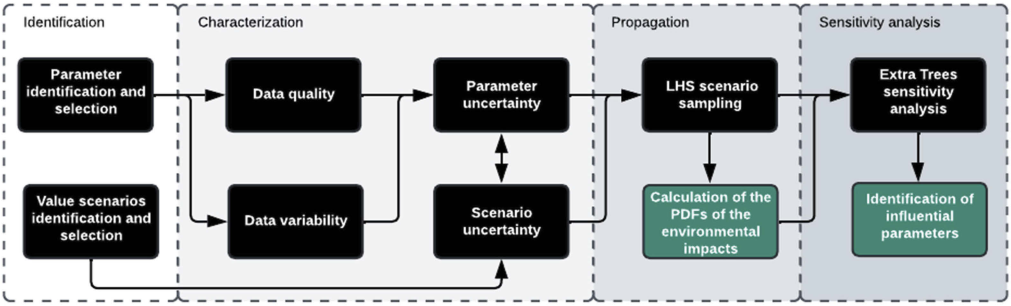


Figure 1. Uncertainty analysis methodology. Black boxes represent the application steps of the methodology, whereas the green ones depict the handling of the outcomes of the methodology.

3 CASE STUDY

The applicability of the proposed framework is illustrated by using the case study of a mill-and-fill M&R treatment for the main road pavement network in the Netherlands. The chosen treatment, selected from a collection of over 75 potential hot mix asphalt overlay options, involves the application of a 50mm-thick layer of Durable ZOAB (DZOAB), which is a porous asphalt mixture with enhanced durability commonly used in the Netherlands.

The functional unit for the analysis is defined as a straight and plan 1km-long carriageway road pavement segment section with 3 lanes, each 3.5km-wide. Traffic data, including average daily intensity values for passenger cars, heavy duty trucks (HDV), and HDV + trailers, were sourced from the INWEVA geographical information system and datasets (Rijswaterstaat, 2022) and are presented in Table 1. The traffic growth rate, set at 1.9%, was determined based on information from the National Statistics Office of the Netherlands (CBS, 2022). The analysis period, corresponding to the average lifespan of a DZOAB surface, is 14 years.

Table 1. Traffic intensity in number of vehicles: statistics.

Vehicle type	Mean	Std	Min	Max
Passenger car	26064	17513	2276	101325
HDV	1744	1035	219	7292
HDV + trailer	2061	1477	140	8872

The system boundaries were adapted from the NL-PCR to align them with the context of M&R (Figure 2), with the exception of leaching, which was excluded from the use phase due to the absence of primary data (Van der Kruk et al., 2022). A construction rate of 1000 ton/day was used in the analysis. Additionally, the environmental benefits of recycling RAP into new pavement materials outside the system boundaries were not considered as RAP enters the system free-of-burden in mixtures with RAP content. Input data for each life cycle phase, except PVI, were obtained from the NL-PCR and the Ecoinvent 3.3 database.

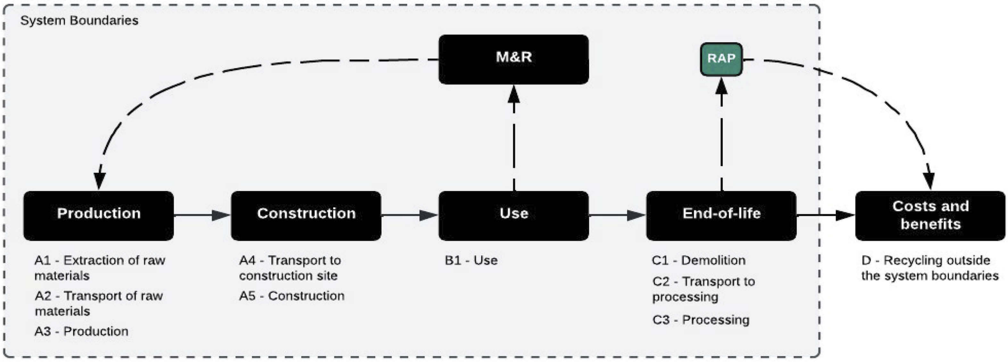


Figure 2. System boundaries of the case study.

The environmental impacts of PVI were calculated using the MIRIAM model (Hammarström *et al.*, 2012). Moreover, linear models were developed for predicting the evolution of roughness and macrotexture over time, respectively represented by the International Roughness Index (IRI) and Mean Profile Depth (MPD), using real IRI and MPD measurements of the Dutch main road network provided by the Dutch Ministry of Infrastructure 'Rijkswaterstaat' (RWS). The values of the parameters of the performance models using pavement age as predictor are presented in Table 2. The results are assumed to follow a normal distribution with a mean corresponding to the predicted IRI and MPD values and a standard deviation (std) equivalent to the mean absolute error (MAE) of the model. Vehicle speeds were determined based on Dutch speed limits (Rijksoverheid, 2022) and were assumed to follow a normal distribution with a mean corresponding to the speed limits and a coefficient of variation of 0.1. For facilitating the calculation and to match the size of the traffic intensity sample of the Dutch road pavement network, approximately 4000 MCS runs were completed to estimate the total additional fuel consumption due to RR over the analysis period. The results follow a normal distribution, and the values of the parameters are presented Table 3. The environmental impacts were then calculated and incorporated into the LCA model using the method described by Santos et al. (2022), which uses the fuel efficiency and environmental impacts of transportation services (excluding the upstream impacts attributed to infrastructure) to model PVI effects.

Table 2. IRI and MPD linear pavement performance models parameters and statistics.

Pavement performance model	Year 0	Annual increase	MAE
IRI (m/km)	0.9993	0.0296	0.0325
MPD (mm)	1.1063	0.0209	0.1207

Table 3. Total extra fuel consumption due to RR in the analysis period (l/km).

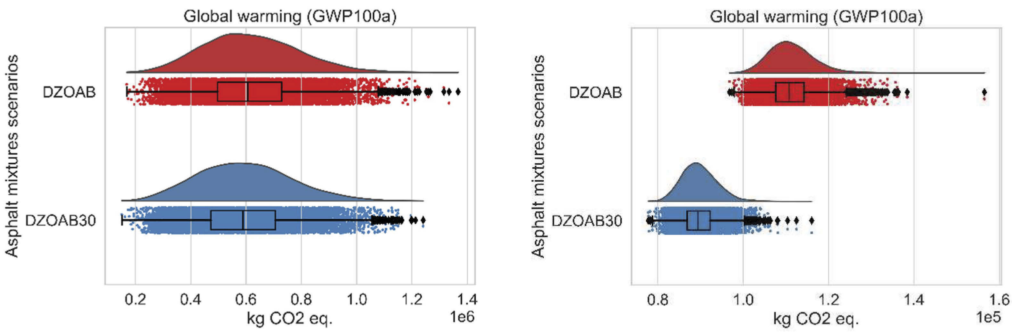
Vehicle type	Mean	Std
Passenger car	68967.84	46675.05
HDV	17729.00	10516.89
HDV + trailer	58536.78	41941.30

The uncertainty analysis was conducted using two scenarios for RAP content: (1) a mixture with 0% RAP and (2) a mixture with 30% RAP. The NL-PCR was used to determine the input values for mixture composition and energy expenditure for asphalt mixtures production, as well as diesel consumption for construction and removal processes, based on the amount of RAP in the mixture (Van der Kruk et al., 2022). All foreground input value parameters assigned to each scenario, including materials, transport, additional vehicle fuel consumption, and energy consumption for production, construction and EOL were considered in the analysis. Data quality uncertainty was calculated using the ecoinvent method (Weidema *et al.*, 2013), as well as the variability of the parameters, with the exception of PVI, whose variability values were computed in the earlier step.

Each scenario was sampled 12,000 times with LHS and environmental impacts of each sample were calculated using the OpenLCA software with a Python interface adapted from the one developed by Jaxa-Rozen et al. (2021b). To identify the most uncertain parameters, an ExtraTrees regression was applied using the scikit-learn Python library (Pedregosa *et al.*, 2012). Finally, given that the environmental impacts of the use phase are expected to be predominant and highly uncertain, two additional scenarios in which one excluded the effects of PVI in module B (use phase) were considered to provide more meaningful insights on the influence of the several parameters on the uncertainty of the outcomes.

4 RESULTS AND DISCUSSION

The environmental impact results for the scenarios including and excluding the use phase are illustrated with the global warming impact category and are presented in Figure 3(a) and (b), respectively. From the analysis of the Figures, it can be seen the use of RAP allows the reduction of the environmental impacts, although this result is almost imperceptible when the use phase is considered. This is due to the overwhelming contribution of the environmental impacts associated with PVI, which outweigh the influence of the remaining phases.



a) b)

Figure 3. Environmental impact for scenarios (a) including PVI effects and (b) excluding PVI effects.

The results of the sensitivity analysis indicate that in scenarios that include the use phase, fuel consumption has the greatest influence on the uncertainty of the outcomes. This can be attributed to the large variability and predominant contribution of extra fuel consumption to the environmental impacts. In contrast, the contribution of other parameters in the scenarios thereof is relatively similar and mostly below the order of 1%. In scenarios that exclude the use phase, there is greater variation in the contributions of different parameters to uncertainty. Notably, transport has a significant effect on uncertainty, particularly the transportation of raw materials via transoceanic ships in module A1, and freight transport to and from the construction site in modules A4 and C2. This can likely be credited to the large uncertainty values assigned to transport exchanges by the ecoinvent method. When taking a closer look at individual life cycle phases, activities related to EOL in module C1, encompassing milling, sweeping and cleaning, and the consumption of natural gas for mixture heating in module A3, are the major contributors to total uncertainty after transport. Finally, when examining the contribution of raw asphalt materials processes in module A1 to total uncertainty, bitumen and large size aggregates present the greatest contributions from this phase.

5 CONCLUSION AND FUTURE RESEARCH WORK

In this study, an LCA framework is proposed for evaluating the environmental impacts of M&R treatments under uncertainty. The key features of this framework include the consideration of PVI in the analysis, the incorporation of parameter and scenario uncertainties in the assessment, and the application of a tree-based ensemble method for sensitivity analysis to determine the most influential parameters in the uncertainty of the outcomes.

The environmental impact results of the case study indicate that when the use phase is considered, the reduction of impacts occurring in other phases becomes imperceptible, even when PVI impact values are relatively low. This substantiates the importance of including the use phase in the analysis, and ensuring that the pavement remain in good condition during the analysis period to reduce extra fuel consumption due to increased RR.

The sensitivity analysis conducted in this study revealed that in scenarios that include the use phase, the contribution of PVI to the uncertainty in the results is overwhelming. In order to gain a deeper understanding of the influence of the various parameters on the uncertainty, further sensitivity analyses were conducted using scenarios that exclude the use phase. The results showed that transportation processes have a significant impact on the uncertainty of the outcomes.

In conclusion, the outcomes of this research work helped to advance the applicability of LCA in the context of pavement M&R, and to improve the understanding of the effects of uncertainties on the outcomes. Further, it offers the possibility of identifying areas with the highest potential for environmental performance improvements by determining the extent to which impacts can be reduced.

Additional research work in this domain will be performed by incorporating other M&R measures beyond asphalt overlays. Additionally, the incorporation of advanced GSA techniques, such as variance-based and distribution-based methods (e.g. Sobol and PAWN), as well as the development of empirical uncertainty factors to account for process variability will be pursued.

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