Uncertainty Analysis of Life Cycle Assessment of Asphalt Surfacings

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Abstract

The Life Cycle Assessment (LCA) of asphalt pavements are associated with significant uncertainty resulting from variability in the quantity and impact of individual components, the quality of data for each component, and variability of asphalt durability. This study presents a framework to quantify and incorporate the uncertainty of LCA and asphalt durability data into LCA of asphalt surfacings. The suggested framework includes: estimating the uncertainty of asphalt production processes by the pedigree matrix method, conducting a deterministic LCA, applying Monte Carlo Simulation (MCS) to estimate the probability density functions (PDFs) of the considered impacts using the uncertainty data, deterministic solution, and asphalt durability. This framework was applied to six asphalt mixtures; the results show that there is significant uncertainty in the processes that contribute to the environmental impacts. They also showed that considering asphalt durability and its uncertainty is critical and can significantly change the results and interpretation of LCA.

Keywords

Life Cycle Assessment; Asphalt; Uncertainty; Durability; Monte Carlo Simulation

1 Introduction

Life Cycle Assessment (LCA) is defined as the assembly of all inputs and outputs of a product system and assessment of all possible environmental burdens over the entire life cycle of the product (BSI, 2013). With respect to asphalt mixtures and their use in asphalt road pavements, this involves inventory of all required raw materials, total energy used, air and water emissions, and the total waste produced during the entire life of the pavement, from cradle to grave. This is a complex system that includes a significant number of different physical, chemical, and mechanical processes that contribute to various environmental impacts during different stages of the life cycle of asphalt. The LCA of asphalt has been investigated extensively in the literature (Chen & Wang, 2018; Harvey et al., 2011; Hoxha et al., 2021; Vidal et al., 2013), as a result of the substantial annual production of this material, which is approximately 300 million tonnes per year in Europe (EAPA, 2018a), and the associated environmental impacts. However, one of the serious criticisms when performing a LCA study is the effects of Life Cycle Inventory (LCI) data uncertainty and variability on the reliability and interpretation of LCA results.

The importance of incorporating LCI uncertainty and variability has been recognised since the 1990's. Bo Pedersen Weidema and Wesnaes (1996) investigated uncertainty of LCI data and introduced two types of uncertainty, basic uncertainty which is related to the variations of an inventory, and additional uncertainty which is related to data quality and can be assessed using the "pedigree matrix" method. Those researchers concluded that low quality data induces bias and increases the uncertainty in impact estimates. Huijbregts (1998) identified LCI data uncertainty and variability as two factors that can make the outcomes of LCA studies questionable. He defined variability as variations between observations, whereas the uncertainty is associated with the lack of confidence in data resulting from inaccurate measurements of the observations, lack of observation data, or model assumptions. Huijbregts et al. (2001) stated that the lack of data and data inaccuracy are the major sources of uncertainty. They introduced a stochastic framework based on Monte Carlo Simulation (MCS) to incorporate LCI data uncertainty in LCA studies.

Existing scientific literature focusing on uncertainty in asphalt pavement LCA shows that there are many studies have been conducted in that field. Tatari et al. (2012) investigated the environmental burdens of different types of warm mix asphalt (WMA) in comparison with a conventional hot mix asphalt (HMA) and conducted a limited uncertainty analysis using MCS to assess the variability of selected inputs. However, this study did not explain how the adopted variability levels of the input data were determined. Noshadravan et al. (2013) developed a numerical model to account for the effects of pavement roughness uncertainty on the global warming impact of asphalt and concrete pavements. The variability of the roughness was calculated using the Mechanistic-Empirical Pavement Design Guide (MEPDG). Then a roughness induced emissions model was deployed to estimate the uncertainty of the global warming impact using MCS. However, the MEPDG software requires accurate calibration with local data, which may limit the implementation of this approach. Vidal et al. (2013) conducted a comparative LCA study on HMA and WMA mixtures with and without incorporation of Reclaimed Asphalt Pavement (RAP). Uncertainty of the inputs was estimated based on the Ecoinvent® database which incorporates the pedigree matrix method. The analysis period in this study was 40 years and the surface layer of the pavement was assumed to be replaced every 15 years. Although this study is comprehensive and accounts for various stages of the asphalt lifecycle, from cradle to grave, the service life was assumed to be equal for all investigated mixtures. AzariJafari et al. (2017) investigated the effects of uncertainty of three sources: scenario uncertainty, variability in construction materials and methods, and parameter uncertainty on LCA of rigid and flexible pavements. These uncertainties were combined and propagated using MCS method. The study demonstrated that the coinciding effects of uncertainty and variability on LCA analysis prevent decision makers from making certain conclusions concerning the environmental impacts of the investigated pavements; and improving inventory data quality is one of the method to reduce uncertainty in the LCA studies. Bressi et al. (2022) implemented CML V4.4 2015 method to study the LCA of cement treated base (CTB) pavement layers contained different recycled asphalt contents using the Open LCA software®; they also conducted LCA uncertainty analysis by MCS method. They concluded that mixed in-place CTM have significantly lower environmental impacts than when mixed in an asphalt plant. The LCA analysis presented in this study however was cradle to gate, which means the use phase, end of life activities, and base layer durability where not considered in the presented analysis. Further studies (Batouli et al., 2017; Cao et al., 2019; Giani et al., 2015; Ziyadi & Al-Qadi, 2018) have also investigated different aspects of LCA uncertainty, mostly by using MCS to propagate the uncertainty of LCA inputs to the results.

The literature reviewed shows the significance of incorporating LCI data uncertainty in the LCA analysis to improve the reliability of results. There is a general agreement on the use of MCS to propagate the inherent uncertainty of LCI data in LCA studies. Despite these efforts, there is a need to develop a more comprehensive framework to handle uncertainty of the different life cycle stages, asphalt durability and its uncertainty on the LCA of asphalt surfacings. Dealing with uncertainty of LCA involves analysing a significant number of processes that contain a great deal of inventories. For instance, there are about 4000 processes relevant at different phases of the pavement life that contribute to global warming potential. Furthermore, one of the important aspects when conducting an asphalt LCA study is the durability of this material when it is used in pavement applications. The durability can be defined as the service life of an asphalt pavement layer, expressed in years, from the construction until major maintenance. It is a complex function of many factors, such as mix volumetric properties, aggregate and bitumen characteristics, mix strength, climatic conditions, traffic loading, structural capacity of the pavement, and construction quality. Therefore, every asphalt mixture has a certain durability; and this point is critical because comparing impact assessment results of two asphalt mixtures will not be valid if they have different service lives unless the durability effect is considered. Furthermore, due to the variability of pavement durability associated with spatial variability of pavement distress (Schwartz, 2007), variability of pavement roughness (Jia et al., 2018), and variability of pavement layer properties (Abed et al., 2019), it is unreasonable to perform an uncertainty analysis of pavement performance disregarding uncertainty in asphalt durability. The scarcity of asphalt pavement durability data could be a critical point when considering this approach, and this situation becomes even more complex when analysing novel asphalt mixtures for which rather limited or no durability data are available. Accordingly, the aim of this study is to develop an LCA framework capable of including uncertainty in inventory data and product durability. The framework is intended to be comprehensive and capable of calculating the probabilistic properties of any considered environmental impact. The following sections describe the development of the framework and demonstrate the application of the derived model to selected case studies.

2 LCA Methodology

The LCA framework developed in this study is represented in Figure 1. The analysis is divided into two main parts: a deterministic LCA, followed by a probabilistic LCA. The first part corresponds to a standard LCA to calculate a central estimate of the considered impacts of all stages and underlying relevant processes over the life cycle. The second one involves MCS to compute probability density functions (PDFs) of the impacts, and sensitivity analysis to identify the inputs and stages with greatest impact on the LCA results. Lastly, the results of these two parts are analysed and interpreted in order to draw conclusions and recommendations from the study.

2. 1 Deterministic LCA

In this part, a standard LCA analysis was conducted in compliance with ISO 14040 (ISO, 2006). The life cycle of asphalt pavement includes four stages: production, construction, use, and end of life as described in the standard BS EN 15804:2012+A2:2019 sustainability of construction works - Environmental product declarations - Core rules for the product category of construction products (BSI, 2019) . The norm gives specific rules for the modelling of construction products in which asphalt is included. Following this norm, the secondary materials enter the system free of environmental burdens and all materials are followed until their disposal or transformation in secondary materials after going through recycling.

In this study, all of these stages were included: the production stage includes the supply, transport, and mixing of raw materials; the construction stage includes all processes related to asphalt paving in addition to its transport from the plant to the construction site; and the end-of-life stage includes asphalt pavement deconstruction processes, namely road surface milling and transportation of the milled asphalt to a waste processing unit where RAP is processed into the desired aggregate grade suitable for the preparation of new asphalt. The milled road surface that is not suitable for asphalt making is disposed of in a landfill for inert materials. The use phase is accounted for in the probabilistic LCA by including the impacts of the major maintenance cycles expected over the analysis period.

Some mixtures contain RAP, which is treated as a secondary material and has no environmental burden allocated to it up to the moment when it reaches the "*end-of-waste status*" in accordance with BS EN 15804:2012+A2:2019 with 100% of its environmental burden being allocated to the first life cycle. In this study, RAP reaches the end-of-waste status after being processed at the Construction and Demolition Waste (CDW) facility. Furthermore, for the deterministic LCA, the functional unit was one metric tonne of surface course asphalt mixture.

2. 2 Probabilistic LCA

The probabilistic LCA is divided into three main steps. Firstly, PDFs of the considered impacts are generated by MCS using ten thousand simulations. To perform this step, three pieces of information are required: the process mean impacts, the uncertainty of the process impacts represented by their Coefficient of Variations (CoVs), and the form of the probability distribution. The impact central estimate values are computed depending on the deterministic LCA described in section 2.1. The uncertainty in data is determined (B P Weidema et al., 2013) as detailed in section 2.2.1; and the PDF is assumed lognormal for all processes. Secondly, the asphalt durability PDF is developed by random sampling. The durability PDF is then used to calculate the PDF of the total quantity of asphalt needed per analysis period, including original construction and subsequent maintenance. Then the PDFs of the considered impacts and total quantity of asphalt are used to calculate the absolute totals of the impacts over the analysis period. Lastly, a sensitivity analysis is run to examine the sensitivity of the model to the input values and to identify the important stages and processes in the analysis.

2.2.1 Uncertainty estimation of LCI data

Uncertainty can be quantified by describing parameters as random variables, in terms of a PDF. If sufficient amount of data that cover the entire distribution of a process exists, then a PDF can be estimated by fitting idealized distributions to the data. However, LCA data are often insufficient or reported in a way that makes it difficult to estimate PDFs purely based on data. To overcome this, Weidema & Wesnaes, 1996 developed descriptive methods to estimate and quantify the uncertainty of data in LCA, when sufficient information is not available. This method has been adopted in the ecoinvent database to quantify the variability of most LCA processes (Muller et al., 2014; B P Weidema et al., 2013) considering two sources of uncertainty; basic uncertainty and additional uncertainty. Basic uncertainty accounts for the aleatory variability, associated with variations between observations, whereas additional uncertainty quantifies the epistemic uncertainty due to lack of quality or extrapolation of data used. In the ecoinvent inventory, a lognormal distribution is generally assumed to model basic uncertainty (B P Weidema et al., 2013) fitted to the existing data. The additional uncertainty is quantified through five quality indicators; reliability, completeness, temporal correlation, geographical correlation, and technological correlation. These indicators have been grouped in one pedigree matrix. Every indicator has a score from one to five, where one represents excellent quality and, consequently, zero additional uncertainty, and a score of five means that there is a high level of additional uncertainty in the data. These descriptive indicators have been interpreted into quantified measures that express the uncertainty in terms of variance of the underlying normal distribution of the data. Therefore, the total variance associated with a material or process is estimated as follows:

$$\sigma^2 = \sigma_{bu}^2 + \sum_{i=1}^{5} \sigma_i^2 \tag{1}$$

where σ^2 is the total variance, σ_{bu}^2 is the basic uncertainty variance, and σ_i^2 (i = 1:5) are the additional uncertainty variances from the pedigree matrix. Further details about this method and its applications can be found in (Muller et al., 2014; B P Weidema et al., 2013).

A key characteristic of this method is that it is data intensive, requiring detailed input data to estimate uncertainty. In the ecoinvent library, these data have been well documented and made available online (Ecoinvent, 2020). For instance, the pedigree matrix to estimate the additional uncertainty of the process *transport, freight, lorry 16-32 metric tonne, EURO4* with respect to Acetaldehyde, which is an exchange to air, is [2; 2; 2; 4; 1]. Different pedigree matrices are available for all types of related exchanges, and the scores of these matrices are determined based on expert judgement (B P Weidema et al., 2013). However, this makes the estimation of uncertainty of LCI data dependent on the inventory and software used; and tracking the uncertainty propagation in this method is a complex process. Accordingly, a new procedure has been developed in this work to extract uncertainty data from the ecoinvent database in a simplified way using SimaPro software. The procedure is as follows:

1. Conduct a deterministic LCA analysis. The impact assessment results will include all processes involved in the analysis and the resulting impacts due to these processes.
2. Identify the processes that account for a joint contribution to all impacts above a predefined threshold (e.g., 95% of all impacts), allowing the reduction of the analysis to a significantly smaller number of processes.
3. Conduct uncertainty analysis on the largest contributors using SimaPro, in order to calculate their CoVs with respect to the considered impacts.

An example of the output of uncertainty data calculated in this method is presented in Table 1. This table shows the CoVs of five selected impacts from three critical processes. In this study, the PDFs of all impacts are assumed to have lognormal distribution. Although this assumption may not reflect the actual distribution of the impacts, this may have a limited effect on the results (B P Weidema et al., 2013).

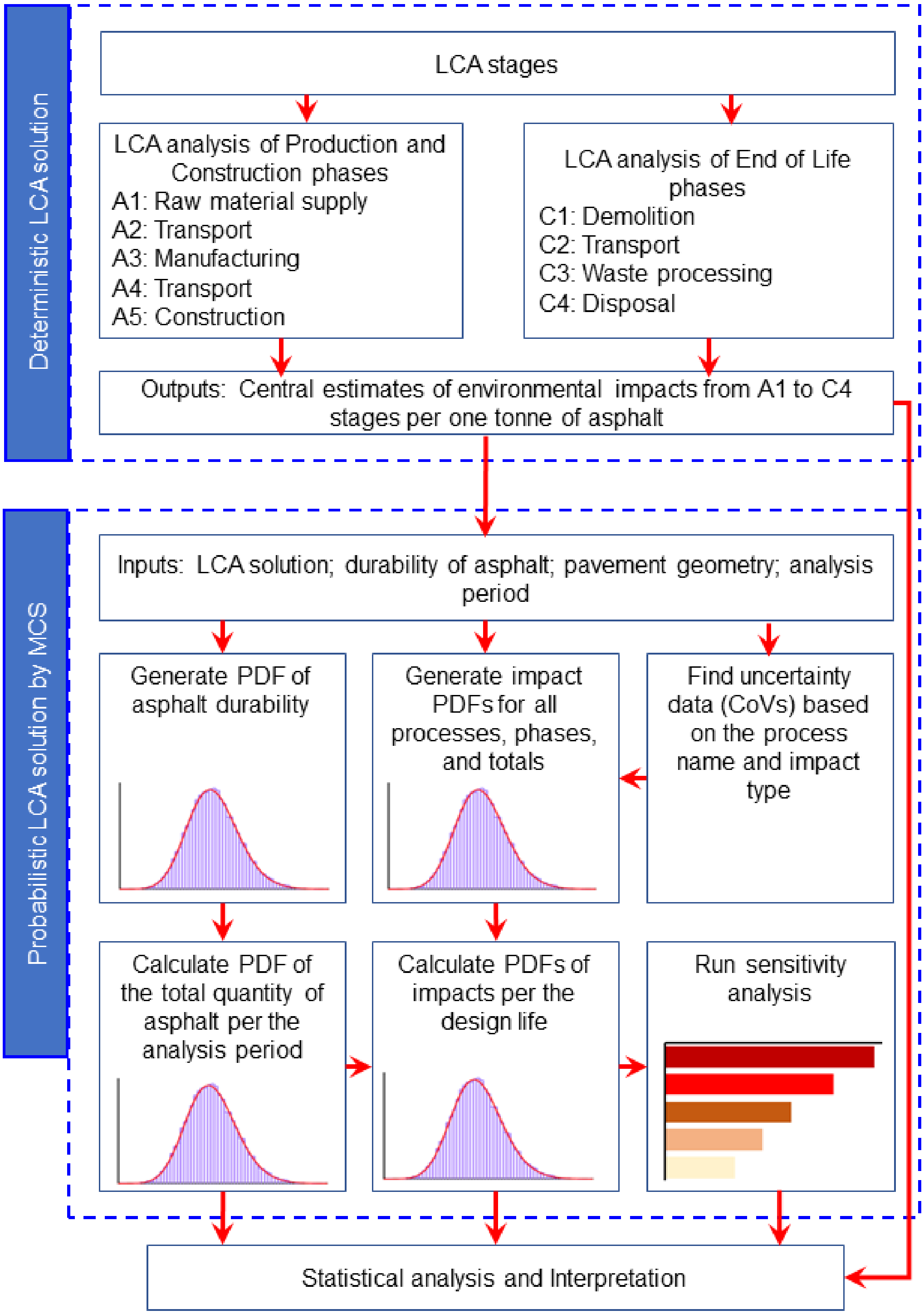

Figure 1. The LCA framework developed in this research

Table 1. Uncertainty of some asphalt production processes with respect to selected environmental impacts, calculated according to the European method CML-IA base line (Guinée & Lindeijer, 2002)

Process	CoV of impacts (%)

	Global warming	Photochemical oxidation	Human toxicity	Ozone layer depletion	Abiotic depletion
Diesel (Europe without Switzerland)| petroleum refinery operation | Cut-off, U	13.86	27.92	34.69	43.09	27.35
Transport, freight, lorry 16-32 metric tonne, EURO4 (RER)| transport, freight, lorry 16-32 metric tonne, EURO4 | Cut-off, U	6.05	19.22	14.67	41.82	43.52
Waste natural gas, sweet (GLO)| treatment of, burned in production flare | Cut-off, U	20.01	90.24	35.02	71.69	59.16

2.2.2 Pavement surface durability

Pavement surface durability represents a key input to the model developed in this study because it is used to estimate the maintenance requirement and hence the total quantity of asphalt required over the analysis period and, consequently, the total environmental impacts. Due to the large uncertainty in the performance of asphalt, especially for new types of asphalt, pavement durability is modelled as a random variable. Durability can be used to estimate the total quantity of asphalt as follows:

$$TQA = (1 + AP\,/AD) \times R_l \times R_w \times L_{th} \times \rho_{as} \tag{1}$$

where TQA is the total quantity of asphalt, AP is the analysis period, AD is asphalt durability, R_l, R_w, and L_{th} are the road length, width and asphalt layer thickness, respectively, and ρ_{as} is asphalt density. The TQA can be used to calculate total environmental impacts as follows:

$$Total\ Impact = TQA \times \sum_{i=1}^{m} \sum_{j=1}^{n} impact\ value_{i,j} \tag{2}$$

where m is the number of phases, and n is the number of processes. The probabilistic distribution of the total impact was computed using MCS implemented in Matlab R2020a.

2.2.3 Sensitivity analysis

In this section the sensitivity of the developed model to the input values is analysed. The sensitivity of the outputs to the input variation can identify the critical LCA stages and processes that cause large variation in the results. In this study a One at a Time (OAT) sensitivity analysis is conducted as:

$$S_{I,P} = (P_{90\%} - P_{10\%})/\sum_{p=1}^{np} S_{I,P} \tag{3}$$

where $S_{I,p}$ is the model sensitivity of impact I with respect to parameter P, $P_{90\%}$ and $P_{10\%}$ are ninetieth and tenth percentiles of the parameter being analysed, the denominator represents the total effect that a group of processes can make when individually varied from 90% to 10%.

3 Case Study

3. 1 Description of asphalt mixtures

Six asphalt mixes were investigated in this study; three are commonly used and the others are novel mixtures yet to find common use and chosen to explore the potential use of LCA in estimating their potential benefits in terms of reduced environmental impacts. The composition of the mixtures and the transportation distance of the used materials are presented in Table 2. SMA 16 ref is a stone mastic asphalt of 16mm coarse aggregate size and is chosen as a reference because of its widespread use in Europe. PA 8 and PA 16 are porous asphalt of 8mm and

16mm coarse aggregate size; they reduce tyre-road noise and are among the most commonly used asphalt mixtures on Dutch highways. Additionally, two SMA mixtures containing Polymer Modified Bitumen (PMB) and RAP along with a longer service life (LSL) SMA were included; the SMA 11 which is a WMA produced at a temperature lower than the reference and containing 40% RAP in mass, the SMA 16 which is a HMA containing 60% of RAP in mass, and the SMA 11 LSL containing a comparatively higher bitumen content and fibres.

Table 2. Material needs in kg per one tonne of asphalt produced.

Materials	SMA 16 ref.*	SMA 11 40% RAP**	SMA 8 60% RAP*	SMA 11 LSL*	PA 8***	PA 16***	Road truck transport (km)*
Bitumen (kg)	55.7			66.0		52.0	160
Polymer modified bitumen (kg)		47.1	34.8		52.0		160
Limestone filler (kg)	70.5	56.7		14.0			0
Hydrated lime filler (kg)					50.0	51.0	0
Fibres (kg)			3.0	3.0		2.0	375
Crushed rock fines (kg)	223.1	169.9		241.0	68.0	43.0	70
Gravel (kg)	650.7	344.0	356.2	676.0	830.0	852.0	70
RAP (kg)		382.0	600.0				70
Additive (kg)		0.3	6.0				1160
Additive type		Organic surfactant	Wax based				-

* (Presti et al., 2015)
** (Varveri et al., 2014)
*** (Vos-Effting et al., 2018)

All of these are bituminous mixtures assumed to be produced at a batch asphalt plant located in the UK, which produces heat from gasoil and does not use a parallel drum to heat RAP separately from the primary materials. Therefore, all aggregates are added to the batch via the cold feed and warmed up together in the hot bins. From the asphalt production life cycle stage onwards, all mixtures have been modelled the same as it was assumed that construction and demolition impacts are independent of the mix type. The transport to the construction site is made by a truck over a distance of 198 km; laying the asphalt consumes 0.57 l diesel per tonne while decommissioning consumes 1.012 l diesel per tonne (Vos-Effting et al., 2018). Half of the RAP is forwarded to a construction waste processing plant where it undergoes a milling process that decomposes it into aggregates of sizes between 19 mm and 0.075 mm, which consumes 0.05 l diesel per tonne of processed RAP (Vos-Effting et al., 2018). The other half of the RAP is assumed to suffer excessive deterioration preventing it from being reincorporated into new asphalt mixtures, it is therefore forwarded to landfill. The durability of SMA 16 ref, SMA 11 LSL, PA 8 and PA16 has been estimated based on previous studies (EAPA, 2018b; Kootstra et al., 2020). Concerning the durability of the SMA mixtures with RAP, these mixtures are still not widely applied in Europe and the authors could not find published data to provide a reliable estimate for their durability. Accordingly, the durability of these mixes was estimated based on expert judgement, collected during the Life Cycle Management of Green Asphalt Mixtures and Road Pavement project, funded by the Conference of European Directors of Roads (PavementLCM, 2020). All other required data for the LCA modelling are presented in Table 3 and Table 4. It must be highlighted here that LCA stages A1-5 and C1-4 use the same inputs for all mixtures, varying only the amount of material transported and laid at the construction site and production temperatures. The frequency these activities take place depends on the maintenance scheme which is explored in the probabilistic analysis.

Table 3. Energy needs, transport, mixing temperature and average service life of one tonne of asphalt throughout its lifecycle

Others	SMA 16 ref.	SMA 11 40% RAP	SMA 8 60% RAP	SMA 11 LSL	PA 8	PA 16
Transport to construction site (km)	198	198	198	198	198	198
Mixing temperature (°C)	150	130	150	150	150	150
Electricity (kWh)	4.80	4.80	4.80	4.80	4.80	4.80
Fuel oil[1]	1.60	1.40	1.60	1.60	1.60	1.60
Expected durability (years)	16	10-14	10-14	20	10	14

Table 4. Process description, energy needs, and transport distances of end-of-life activities

End of life phase	SMA 16 ref.	SMA 11 40% RAP	SMA 8 60% RAP	SMA 11 LSL	PA 8	PA 16
C1 - decommissioning	During decommissioning the following machines were used considering a production of 150 tonnes asphalt per hour and a consumption of 1.012 litres diesel per tonne. • Milling machine 403 kW • Sweeping truck 300 kW • Road cleaner 400 kW					
C2 – transport (km)	56	56	56	56	56	56
C3 - recycling	The milling process decomposes the asphalt layer into particles varying composition and sizes, between 19 mm and 0.075 mm or smaller. In this study it is presumed that half of the RAP is forwarded to the asphalt plant to undergo screening using a Power screen™ Chieftain 1400 which will enable its recycling in a new life cycle and half of it is disposed at a landfill. This machine can process 400 tonnes of RAP per hour and its stage 4 version has a peak power of 131 hp. Considering a nominal fuel consumption of 0.15 litres diesel per hp per hour the machine consumes 19.65 litres fuel per hour while processing 400 tonnes, thus the total fuel consumption to process 0.5 tonne RAP amounts to 0.025 litres diesel.					
C4 – disposal (km)	56	56	56	56	56	56

3. 2 Model application

The deterministic LCA analysis was performed using SimaPro software based on the European impact assessment method CML-IA baseline (Guinée & Lindeijer, 2002). By this method, eleven environmental impacts are calculated. However, three of them were selected in this study due to their relative importance and also to demonstrate the model application: Global Warming Potential; Photochemical Oxidation; and Eutrophication. Global Warming Potential expresses the contribution of greenhouse gas emissions to global warming and is measured in mass of carbon dioxide equivalents (CO_{2eq}). Photochemical Oxidation is one form of air pollution caused by the reaction of sunlight with fossil fuel combustion emissions and is measured in mass of ethylene equivalents (C_2H_{4eq}). Eutrophication is the impact of emitting nitrogen (N) and phosphorus (P) to the atmosphere, which is subsequently deposited in surface soils and water affecting the health of freshwater and marine ecosystems and is measured in mass of phosphate equivalents ($PO_4{}^{3-}{}_{eq}$) (Morelli et al., 2018). It must be stated here that although only these impacts are reported in this study, the developed framework can be applied to investigate any impacts. To limit the number of processes to consider in the analysis, a cut-off threshold of 2% is used. This means that all processes contributing less than this threshold to the selected impacts are reported as "remaining processes". SimaPro is then used to compute the mean and CoV of the impact of each of these processes in each impact indicator. This information is combined with durability data to estimate the PDFs of the selected impacts. Finally, a sensitivity analysis was performed using the OAT method to identify the processes and phases that most contribute to the impacts.

3.2.1 Deterministic LCA analysis results

Using the data shown in Table 2, Table 3, andTable 4, the six mixtures were analysed using SimaPro software. The mean value of the impact factors, in terms of Eutrophication, Global Warming Potential and Photochemical Oxidation are shown in Table 5. With the incorporation of RAP, the environmental impacts of one tonne of asphalt are expected to decrease due to the use of secondary materials free of environmental burdens (Bizarro et al., 2021; Gulotta et al., 2019). However, the LCA results associated with the two mixtures containing 40% and 60% RAP showed higher environmental impacts than all other mixtures except for the PA 8 mix. This can be explained by two major differences between these mixtures and the others. Firstly, both mixes containing RAP also contain PMB, which has higher impacts in the three categories (0.00068 kg PO_4 eq., 0.724 kg CO_2 eq., and 0.00028 kg C_2H_4 eq. per kg PMB) in comparison with regular bitumen (0.00044 kg PO_4 eq., 0.426 kg CO_2 eq., 0.00025 kg C_2H_4 eq. per kg bitumen). Notably, the binder alone is responsible for 80% of the environmental impacts from life cycle stages A1-A3 for all mixtures and the three impact categories. Thus, using PMB offsets the environmental impact reduction achieved with the use of RAP. In fact, RAP can lower the environmental impacts of asphalt mixtures but also the performance of the mix (Kodippily et al., 2016). In order to mitigate part of the performance loss, mixes containing RAP may use PMB instead of regular bitumen, as explained by Santos et al. (2018). According to this author, the technical performance can be improved with PMB in HMA which reduces the need for maintenance and rehabilitation cycles consequently reducing environmental impacts of surface courses. The production of SMA mixtures with high recycled content is an innovative technology under development and as such it is not clear whether using PMB would allow them to reach the same service life as mixtures containing solely primary materials. Therefore, applying PMB may result in lower environmental impacts provided that the durability of the RAP containing mixtures becomes longer than the reference. Secondly, both mixes containing RAP also include rejuvenating additives, which have high environmental impacts. Table 5 shows that PA8 mix has larger impacts for Eutrophication and Global Warming Potential than all the other mixes, this can be attributed to the high content of PMB (5.2% in mass).

Table 5. Eutrophication, Global Warming Potential, and Photochemical Oxidation estimates for one tonne of the mixtures

Mix \ Impact	Eutrophication (kg PO_4 eq)	Global Warming Potential (kg CO_2 eq)	Photochemical Oxidation (kg C_2H_4 eq)
SMA16 ref	0.1163541	96.56678	0.027198
SMA11-40%RAP	0.1664254	106.47234	0.026649
SMA8-60%RAP	0.1458065	101.45136	0.023708
SMA11 LSL	0.1222149	101.95172	0.030044
PA8	0.1752549	110.74094	0.027906
PA16	0.1158164	95.95976	0.026572

3.2.2 Uncertainty quantification results

Following the methodology developed in this study, the uncertainties of the largest contributing materials and processes to the LCA results were quantified. In total, twenty-two primary contributors were identified in this study and the uncertainty of these processes with respect to the selected impacts were calculated as shown in Table 6. There are significant variations in the CoV across the processes and impacts. This is because every process contributes to each particular impact differently. For instance, in process number eight, the CoV with respect to the Photochemical Oxidation impact is 122.21%, which is significantly high. This means that the LCI data for this process, that contribute to the Photochemical Oxidation impact have a high level of uncertainty. On the other hand, the Global Warming Potential CoV of process nineteen is 6.05%, which means the LCI data contributing to that impact have low uncertainty levels. However, the Eutrophication CoV of process eleven is 0%, which means that this process does not contribute to that particular impact. Furthermore, this Table shows that the Photochemical Oxidation has larger CoVs than for the other impacts, whereas the Global Warming Potential has the lowest CoVs amongst the studied impacts. However, the CoVs of all investigated impacts can be considered as significant and must be considered in the interpretation of the LCA results.

Table 6. Uncertainty of the largest contributor processes

Process number	Process name	CoV%		
		Eutrophi-cation	Global Warming Potential	Photoche-mical Oxidation
1	Diesel [Europe without Switzerland]| petroleum refinery operation | Cut-off, U	28.26	13.86	27.92
2	Diesel, burned in building machine [GLO]| processing | Cut-off, U	20.15	8.72	36.46
3	Diesel, burned in diesel-electric generating set, 10MW [GLO]| diesel, burned in diesel-electric generating set, 10MW | Cut-off, U	82.26	17.35	57.20
4	Heat, central or small-scale, other than natural gas [RoW]| heat production, anthracite, at stove 5-15kW | Cut-off, U	60.14	17.22	77.60
5	Heat, district or industrial, natural gas [Europe without Switzerland]| heat production, natural gas, at industrial furnace >100kW | Cut-off, U	27.84	17.22	24.12
6	Heat, district or industrial, other than natural gas [CH]| refinery gas, burned in furnace | Cut-off, U	62.58	9.77	92.13
7	Heat, district or industrial, other than natural gas [Europe without Switzerland]| heat production, light fuel oil, at industrial furnace 1MW | Cut-off, U	33.38	18.97	38.14
8	Heat, district or industrial, other than natural gas [Europe without Switzerland]| refinery gas, burned in furnace | Cut-off, U	54.97	9.92	122.12
9	Heat, district or industrial, other than natural gas [RoW]| heat production, at hard coal industrial furnace 1-10MW | Cut-off, U	36.61	17.57	6.65

10	Heavy fuel oil, burned in refinery furnace [Europe without Switzerland]| processing | Cut-off, U	17.85	4.07	32.23
11	Natural gas, vented [GLO]| natural gas venting from petroleum/natural gas production | Cut-off, U	0.00	22.73	22.75
12	Petroleum [RU]| production, onshore | Cut-off, U	43.30	26.80	4.39
13	Pitch [CH]| petroleum refinery operation | Cut-off, U	33.19	19.24	22.50
14	Sinter, iron [GLO]| production | Cut-off, U	36.95	14.93	76.95
15	Spoil from hard coal mining [GLO]| treatment of, in surface landfill | Cut-off, U	60.88	44.47	9.68
16	Spoil from lignite mining [GLO]| treatment of, in surface landfill | Cut-off, U	59.16	22.34	20.42
17	Sulfidic tailing, off-site [GLO]| treatment of | Cut-off, U	71.20	8.88	21.27
18	Sweet gas, burned in gas turbine [RoW]| processing | Cut-off, U	19.75	20.69	112.92
19	Transport, freight, lorry 16-32 metric tonne, EURO4 [RER]| transport, freight, lorry 16-32 metric tonne, EURO4 | Cut-off, U	16.19	6.05	19.22
20	Transport, freight, sea, transoceanic tanker [GLO]| processing | Cut-off, U	18.52	15.64	17.78
21	Waste natural gas, sour [GLO]| treatment of, burned in production flare | Cut-off, U	20.50	20.94	22.14
22	Waste natural gas, sweet [GLO]| treatment of, burned in production flare | Cut-off, U	19.24	20.01	90.24

3.2.3 Probabilistic LCA analysis results

By combining the deterministic analysis results (Table 5), the uncertainty data (Table 6), and the durability data (Table 3), it is possible to estimate the probability distribution of the impacts of each asphalt mix. However, since the PDFs of the durability data of the mixtures are not available, then these data were determined based on expert opinion. It was assumed that the durability range for SMA11 40% RAP and SMA8 60% RAP in Table 3 represent the 5^{th} and 95^{th} percentiles of the durability distributions. For other mixes, the available durability data are assumed central estimates; then the 5^{th} and 95^{th} percentiles were assumed to be the central estimates ± three years. This assumption is necessary to estimate the durability probability distribution of the mixes, and the assumed numbers can be readily updated in the future when more performance data will be available. By following this assumption, the durability standard deviation of every mix was estimated, and Figure 2 was developed. By using the durability PDFs and applying equation 2, the PDFs of the total quantity of asphalt of every mix over forty years was calculated, as shown in Figure 3. As expected, mixes with longer durability are associated with lower life-cycle material quantities and, potentially, with lower life-cycle environmental impacts.

Furthermore, Figure 4,Figure 5, andFigure 6 present the results of the Eutrophication, Global Warming Potential, and Photochemical Oxidation impacts, respectively. These figures indicate that there is a direct relationship between the TQA and the environmental impacts. For instance, mix PA8 has the largest mean impacts and largest standard deviation of all mixes (see Figures 4 to 6), which is a direct consequence of the large TQA (Figure 3) due to the low estimated durability (Figure 2). On the other hand, the SMA11 LSL mix showed the lowest mean impacts and lowest standard deviation, due to the longest durability and therefore, the lowest amount of materials used (TQA). The other mixes show similar trends. This demonstrates the critical role of asphalt durability in the potential environmental impacts and their variability. Improving asphalt durability not only reduces the mean environmental impacts, but also the uncertainty in LCA results.

The results in Figures 4, 5, and 6 show that there is a considerable overlap in the PDFs of the impacts amongst different mixes. For instance, regarding Eutrophication, SMA11 LSL mix has the lowest mean impact, but there is significant overlap with SMA16 ref and PA16. SMA8-60% RAP and SMA11-40%RAP also showed similar trends and both of these mixtures have a clear overlap with the PA8 mix. Concerning the Global Warming Potential impact, similar trends can be identified. Photochemical Oxidation results show greater uncertainty (see Table 6) and consequently, larger overlap amongst mixtures than for the other impacts.

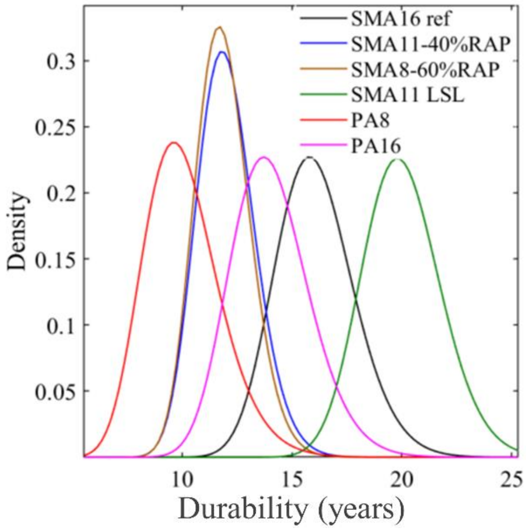

Figure 2. Durability PDFs of the mixtures

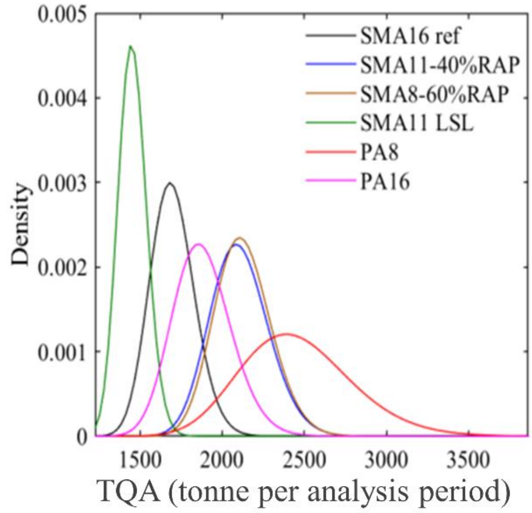

Figure 3. TQA PDFs over 40 years

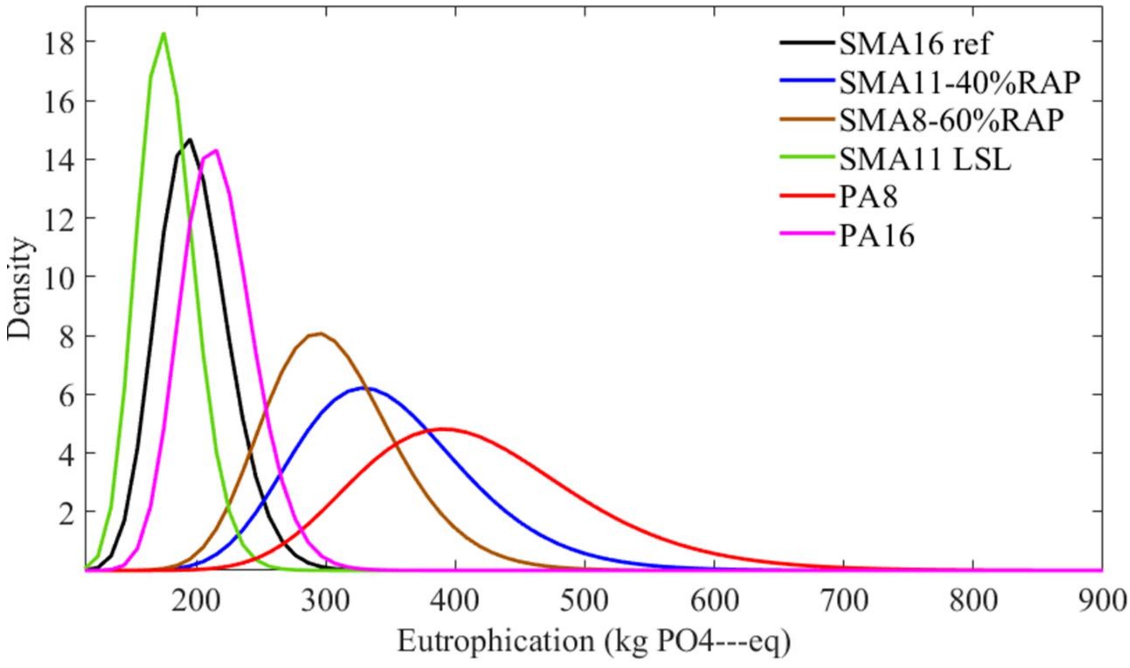

Figure 4. Eutrophication total impact over 40 years

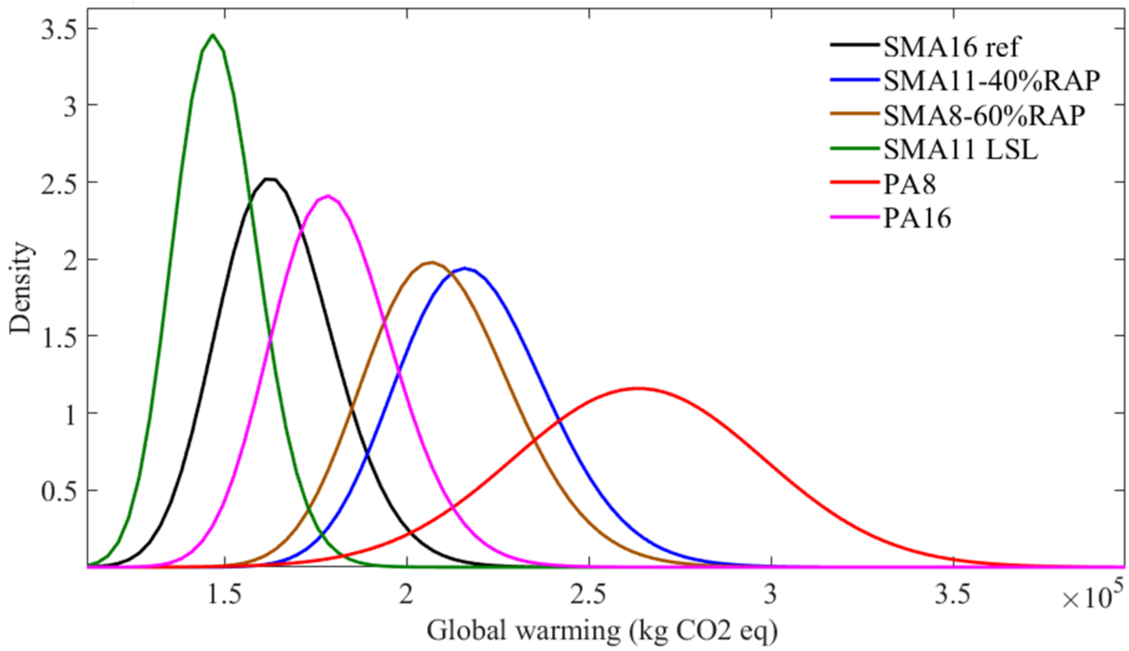

Figure 5. Global Warming Potential total impact over 40 years

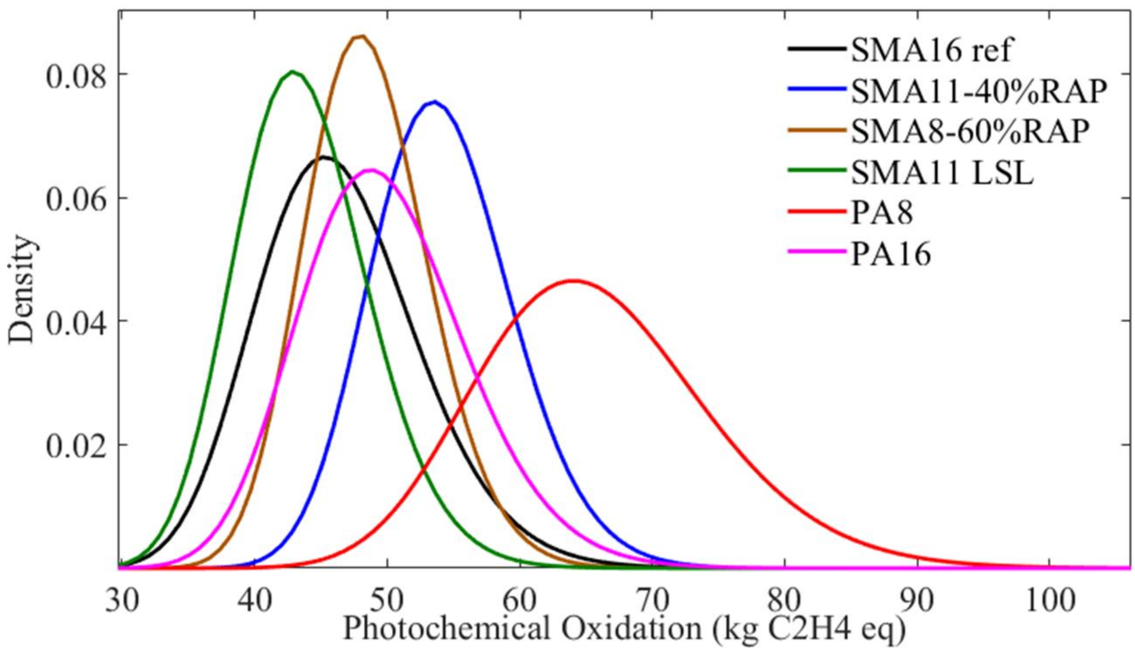

Figure 6. Photochemical Oxidation total impact over 40 years

3.2.4 Sensitivity analysis results

Following the OAT methodology explained earlier, the stages and processes that have significant effects on the calculated impacts were identified, as shown in Figures 7 to 12. The greater Eutrophication impacts arise from processes in the raw material supply stage with overall weight between 33 to 58% depending on the mix (see Figure 7). Eutrophication is also impacted by the processes in the transport stage but to a lesser extent. Global Warming Potential is mostly affected by the processes in the transport stage (A4), followed by stages: raw materials supply (A1), transport to plant (A2), manufacturing (A3) and transport to waste processing site (C2) to lesser extents. On the other hand, Figure 9 indicates that the Photochemical Oxidation impact is dominated by the processes in stage A1 with overall effect between 50 to 70%. This figure also shows that stage A4 has effects between 13 to 20% for this impact, whereas other stages have a limited effect of less than 10%.

Figures 10 to 12 present the first three critical processes sorted by importance. Figure 10 shows that the Eutrophication impact is fundamentally sensitive to the transport by land, Spoil from Lignite mining, and Spoil from hard coal mining. Global Warming Potential is most sensitive to the transport by land process; it is also sensitive to the heat production and diesel burned in building machine processes but to a lesser extent. Photochemical Oxidation is mainly affected by pitch refinery operation, waste natural gas, and diesel burned for petroleum refinery process.

These results can be used to investigate the possibility of reducing the environmental impacts and, particularly, the uncertainty in LCA results. For instance, to reduce the uncertainty in Global Warming Potential during LCA, it is fundamental to reduce the uncertainty in impacts resulting from the transport process, by improving the estimates of travel distance and the type of truck used.

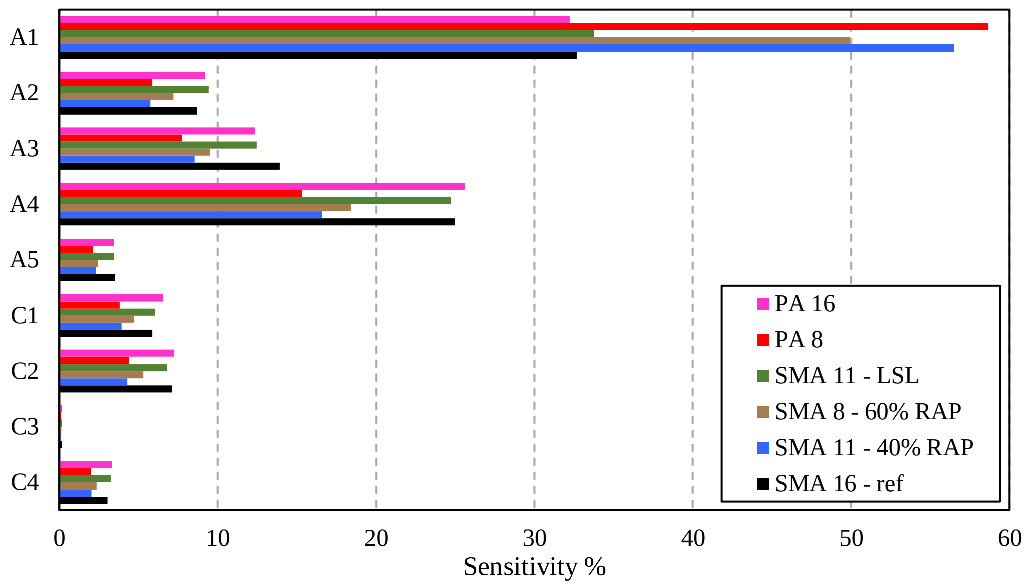

Figure 7. Sensitivity of Eutrophication to the LCA stages

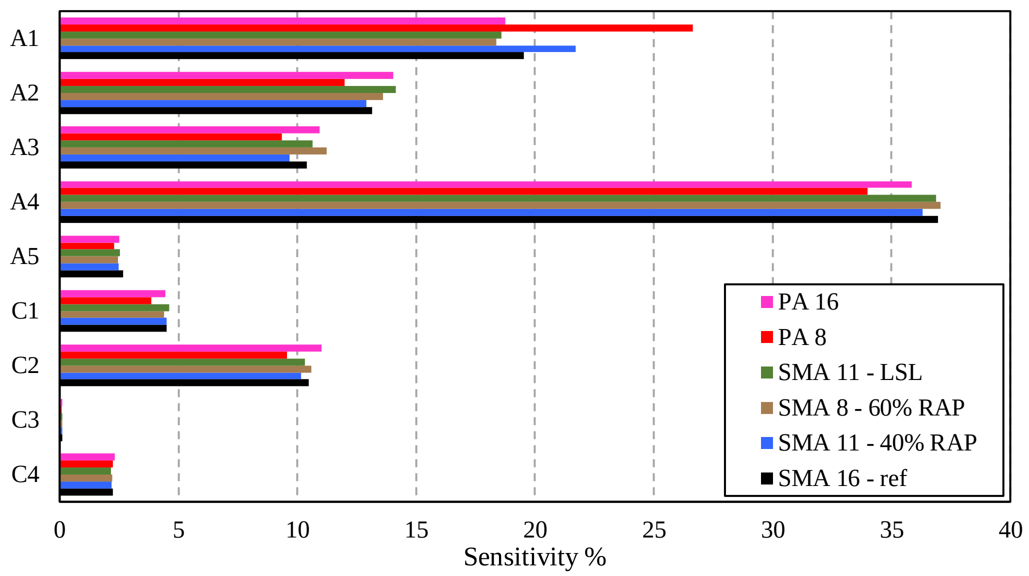

Figure 8. Sensitivity of Global warming to the LCA stages

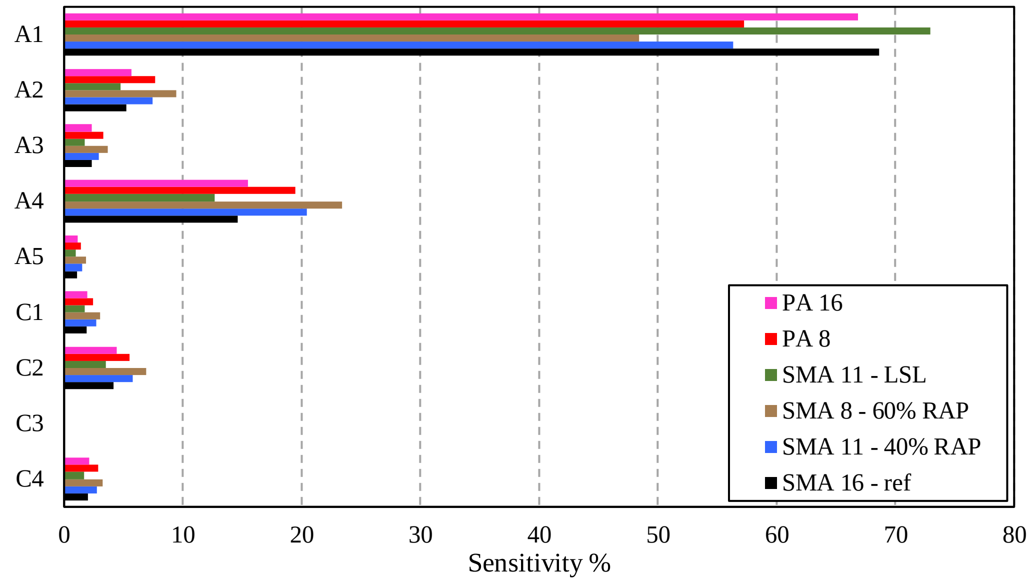

Figure 9. Sensitivity of Photochemical oxidation to the LCA stages

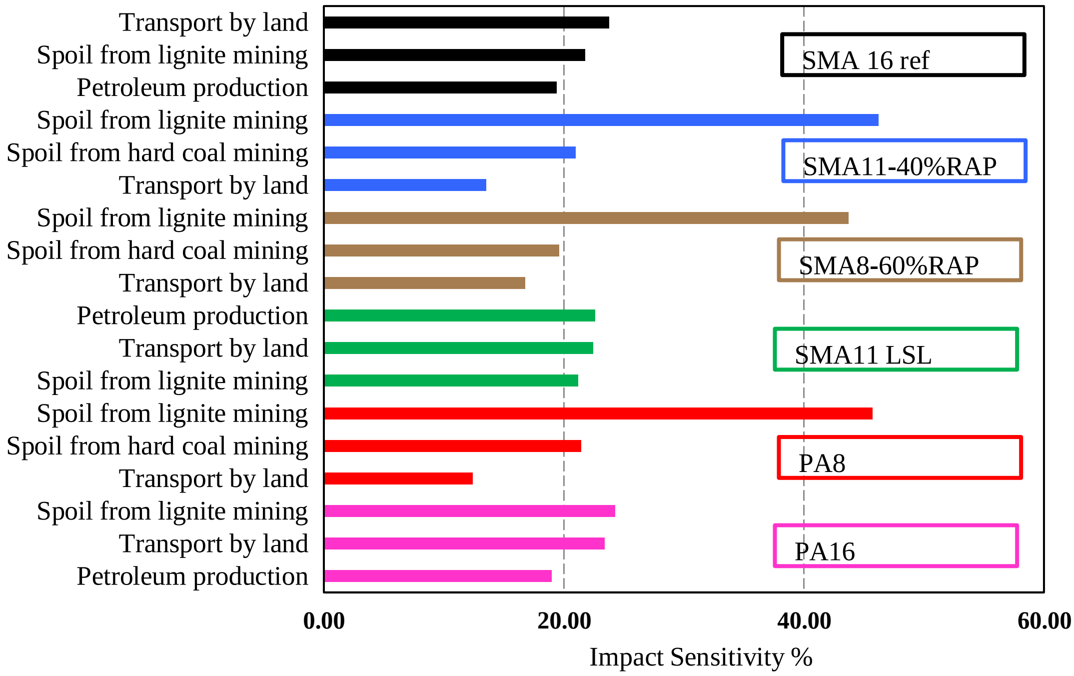

Figure 10. Sensitivity of Eutrophication to the relevant processes

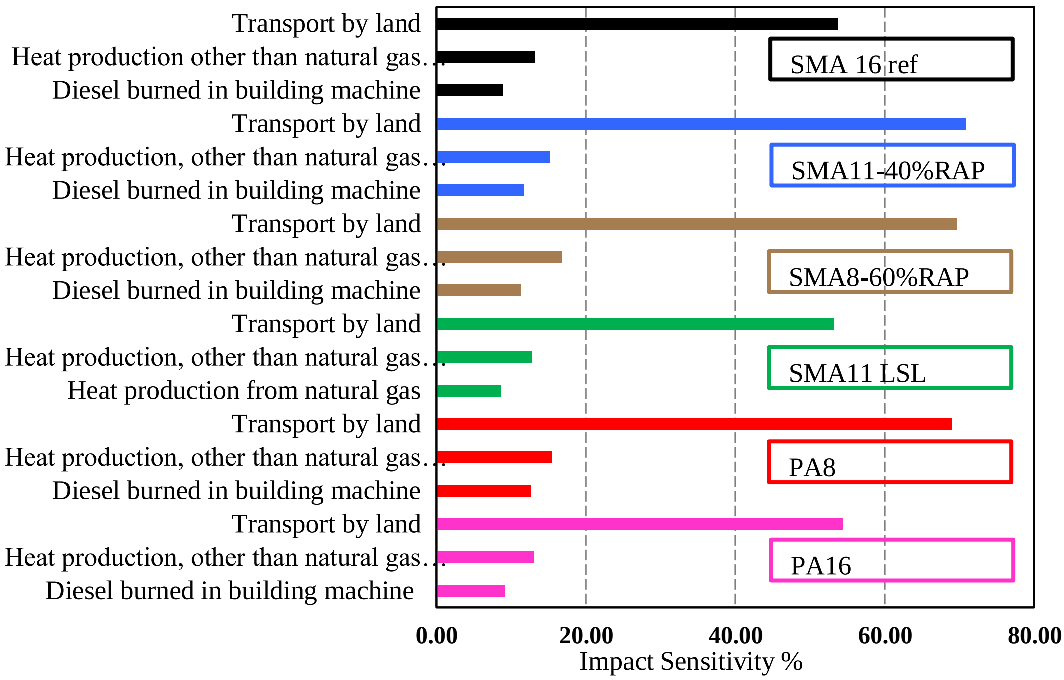

Figure 11. Sensitivity of Global Warming Potential to the relevant processes

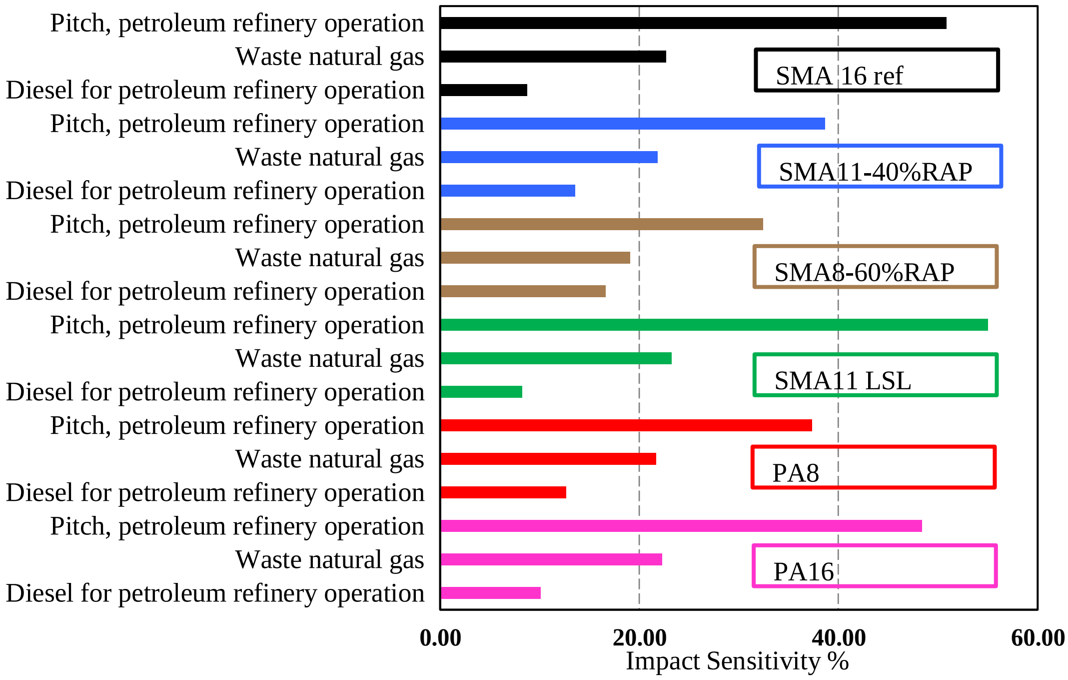

Figure 12. Sensitivity of Photochemical Oxidation to the relevant processes

4 Statistical analysis and interpretation of results

In this section, the PDFs of the studied impacts, shown in Figures 4, 5 and 6, were statistically analysed. To achieve this, firstly, an ANOVA test was conducted to test the significance of the differences between estimates of the mean impacts. This test showed that at least one result was significantly different at a significance level of 5%. Therefore, series of T-tests were conducted across all data to identify the significantly different cases. The T-test results indicated all distributions were different at a significance level of at least 5%. Lastly, a Kolmogorov-Smirnov test was conducted to test the difference between the impact PDFs of all mixtures in pairwise comparisons. The null hypothesis is that the two tested samples are from the same distribution. The alternative hypothesis is that the test samples are from two different distributions. Table 7 presents the results of this test where zero means the null hypothesis is accepted and the two tested datasets are from the same distribution, and one means the null hypothesis is rejected and the two tested datasets are from different distributions. These results also indicate that impact PDFs of all mixes were from different distributions.

Furthermore, Figure 4 toFigure 6 show that LCA results have a significant variability, which means there is a high risk of underestimating the environmental impacts if the mean values are used. An approach to manage this risk is to define the environmental impacts associated with a certain reliability level. This approach can reduce the risk of underestimating the impacts and enhance the reliability of LCA results. In this study, a reliability level of 90% was used as shown in Table 8. These results indicate that, at this reliability level, the SMA11 LSL mix was associated with lower environmental impacts, as a result of its longer durability. It is followed by SMA16 ref which is also associated with the second largest durability (central estimate of 16 years). The mix with the highest impacts is PA8, which also has the lowest durability (average 10 years). Furthermore, by comparing the results over the analysis period with those in Table 5 for one tonne of the asphalt mixes, it can be seen that the ranking of the mixtures has changed, as shown in Figure 13. This Figure shows the ranking of the mixtures based on impact level from one to six, where one means lowest impact and six means highest. It can be seen that analysing the LCA results based on impact estimated over the analysis period leads to a different ranking to that for one tonne of asphalt mixes. The Figure also shows that the ranking of SMA16 ref and PA16 has fallen whereas that for SMA11 LSL has improved when ranking the mixtures with respect to the expected impact over the analysis period; which shows the importance of durability and analysis over an extended duration.

These interpretations are based only on the three selected environmental impacts. For instance, if the Energy Consumption (EC) impact was selected in this study, then the mixes with 40% and 60% RAP could outperform other mixes since RAP incorporation can decrease EC (Aurangzeb et al., 2014). The same could apply if the life cycle cost impact was considered since RAP incorporation can reduce asphalt production cost (Qiao et al., 2019). Accordingly, to better interpret LCA results, especially in the situations where the analysed mixes show contradicting impact results, a multi-criteria decision-making analysis may be required to identify the mix that best matches the desired decision-making criteria (Bryce et al., 2017).

Table 7. Kolmogorov-Smirnov test results

Eutrophication	SMA16	SMA11-40% RAP	SMA8-60% RAP	SMA11 LSL	PA8	PA16
SMA16	0	1	1	1	1	1
SMA11-40%RAP	1	0	1	1	1	1
SMA8-60%	1	1	0	1	1	1
SMA11 LSL	1	1	1	0	1	1
PA8	1	1	1	1	0	1
PA16	1	1	1	1	1	0
Global Warming	SMA16	SMA11-40% RAP	SMA8-60% RAP	SMA11 LSL	PA8	PA16
SMA16	0	1	1	1	1	1
SMA11-40%RAP	1	0	1	1	1	1
SMA8-60%	1	1	0	1	1	1
SMA11 LSL	1	1	1	0	1	1
PA8	1	1	1	1	0	1
PA16	1	1	1	1	1	0
Photochemical oxidation	SMA16	SMA11-40% RAP	SMA8-60% RAP	SMA11 LSL	PA8	PA16
SMA16	0	1	1	1	1	1
SMA11-40% RAP	1	0	1	1	1	1
SMA8-60% RAP	1	1	0	1	1	1
SMA11 LSL	1	1	1	0	1	1
PA8	1	1	1	1	0	1
PA16	1	1	1	1	1	0

Table 8. Impact results at 90% reliability level

Mix \ Impact	Eutrophication (kg PO4--- eq)	Global Warming (kg CO2 eq)	Photochemical oxidation (C2H4 eq)
SMA16 ref	233.46	185,147	54.50
SMA11-40%RAP	445.18	251,251	63.33
SMA8-60%	397.30	240,528	56.25
SMA11 LSL	208.46	164,061	51.30
PA8	559.05	314,876	79.51
PA16	255.14	203,712	58.50

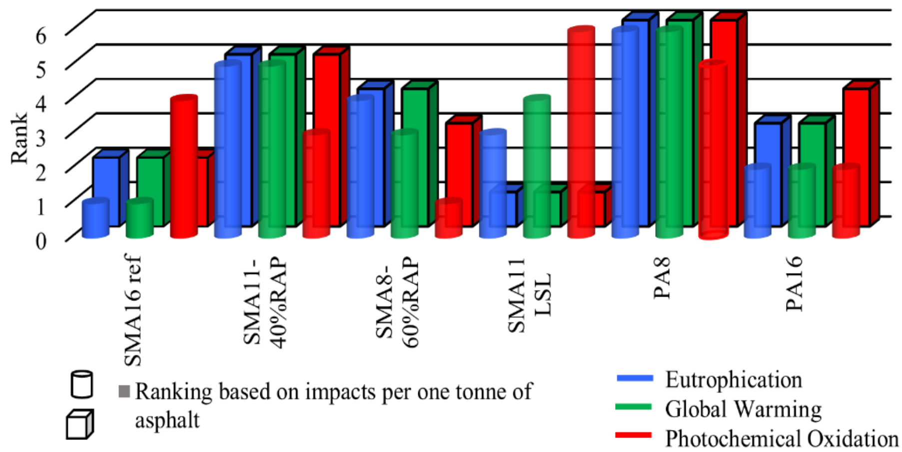

Figure 13. Ranking results for alternative mixes

5 Conclusions and recommendations

Uncertainty in the data required for performing LCA has been reported as one of the main factors limiting the quality and interpretation of LCA studies and this is particularly the case for new products where performance data is naturally limited. In this study, uncertainty in the LCA of asphalt used in road surfacing was investigated and a new model accounting for uncertainty of critical contributing materials and processes was developed based on the Monte Carlo Simulation method. The model comprises two main stages. Firstly, a deterministic analysis, in which the impacts per unit (tonne) of asphalt are calculated. Secondly, a probabilistic analysis stage in which precalculated uncertainty of the most impactful materials and processes involved in the analysis, as well as material durability, are incorporated to calculate the probability density functions of the predicted impacts over the desired analysis period. To demonstrate the application of the developed model, a case study of six asphalt mixtures used in Europe was analysed. The LCA deterministic analysis of these mixes was performed in accordance with the standard BS EN 15804:2012+A2:2019 using SimaPro software; the life cycle of asphalt consisted of production, construction, and end of life activities. The probabilistic analysis allowed the calculation of the PDF of the total quantity of asphalt for the analysis period. Based on the results of this study, the following conclusions can be drawn:

- The results show that there is significant uncertainty in most of the processes involved in the production, construction, and end of life activities of asphalt, which in one case reached a Coefficient of Variation of 122%. This means that the predicted environmental impacts also have significant uncertainty.
- These results show that the variability in environmental impact predictions makes the interpretation of the LCA results more complex, showing that uncertainty must be considered in the LCA data interpretation to achieve robust and reliable decisions.

- LCA studies should incorporate uncertainty of the most impactful materials and processes involved in the analysis, and their effects on the predicted environmental impacts. This is necessary to improve the confidence in interpretation of LCA and to increase the credibility of any conclusions drawn regarding the sustainability of asphalt.
- Durability of asphalt has a critical effect on the estimation of the overall LCA impacts of this material. More durable mixtures can have lower environmental impacts due to the reduced amount of asphalt consumed over the analysis period. Therefore, to include asphalt durability in the analysis developed in this study, durability data, expressed as years from laying the asphalt until the first major maintenance cycle, should be well documented by national road authorities and highway agencies.
- Sensitivity analysis results showed that global warming is significantly affected by transport by land processes. This means that cutting transport emissions not only reduces the risk of global warming, but it can also reduce the uncertainty in LCA results, which lead to making more confident decisions when analysing LCA results.
- The results of this study have not been compared with other LCA studies as these results are for the implemented case studies which have specific mix designs and service lives. The developed LCA framework, however, is valid to analyse any asphalt surfacing as long as the required data is available and it is applied in the described method.
- LCA uncertainty and LCA analysis period are two critical factors ton consider in any LCA study. This is because relaying on the central estimate of LCA impacts may lead to wrong conclusions. For instance, based on the deterministic solution shown in Table 5, SMA11 LSL has more negative environmental impacts than the reference mix, and it would have been disregarded if one needs to decide based on this table solely. When including LCA uncertainty and the analysis period in the analysis, however, we can confidently conclude that SMA11 LSL in fact has less environmental impacts than all other mixes, which explains the necessity to perform the suggested approach.

Lastly, it must be stated here that the environmental analysis of the studied mixtures was conducted using three environmental impacts selected due to their relative importance. However, to obtain a full understanding concerning the sustainability of these mixtures or any other asphalt mix, further environmental, economic, and social impacts should be considered; and a multi-criteria decision-making approach should be implemented to analyse the chosen sustainability indicators and identify the most sustainable options. Moreover, although the developed framework is comprehensive, it involves the use of various tools such as LCA software, LCA databases, quantification of LCA processes' uncertainties, and writing a code to calculate the impact PDFs, which may limit the implementation of this approach. The develop approach also did not address any method to assess the quantified uncertainties of LCA processes. This is due to the lack of data and information on the sources and magnitude of uncertainties in these processes. Further, this study did not cover the effects of pavement performance during its service life on vehicle fuel consumption. Asphalt properties and pavement structure have critical effects on pavement performance and the roughness of the road surface, which can have critical impacts on the overall LCA results.

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Conflicts of Interest: The authors declare no conflicts of interest.

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Data Availability: Any further data can be made available on request.

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