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Selecting the optimal network-level pavement maintenance plan based on sustainable considerations

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Abstract: This study aims to integrate sustainability indicators into the traditional assessment of network-level pavement maintenance plans. A conceptual framework is developed based on a multi-attribute method by systematically considering road conditions, economic, environmental, and social sustainability. A case study is then adopted to demonstrate the usefulness of this framework. Out of eight network-level pavement maintenance plans, the 85M plan (representing an annual maintenance budget of AUD$85M) is selected as the optimal solution in an initial experiment in which equal weights are allocated to the four attributes. In an additional experiment with 1000 sets of randomly assigned weights, the 85M plan was also selected as the optimal option for 596 trials. The proposed framework provides a straightforward method for road agencies to select the optimal network-level pavement maintenance plan or obtain preliminary insights when the precise weight of each sustainability attribute cannot be accurately obtained.

Keywords: Pavement maintenance plan; life cycle assessment (LCA); carbon footprint; social sustainability; sustainable road pavements; sustainable development

1. Introduction

An infrastructure asset requires large capital investment and ongoing operation and maintenance costs. Roads represent one of the most expensive and comprehensive infrastructure assets in the architecture, engineering, and construction sectors. In 2017, the American Society of Civil Engineers (ASCE) published a report related to the infrastructure status of the U.S. and found that U.S. roads are chronically underfunded, with a $90 billion rehabilitation need, and one of every five miles of highway is poorly maintained (ASCE, 2017). In addition, the Australian Government spends more than AUD$7 billion annually on maintaining and renewing roads (Department of Infrastructure and Transport, 2014). Road maintenance consists of routine maintenance, preservation, and pavement rehabilitation (Torres-Machi et al., 2018). Routine maintenance usually consists of reactive and corrective actions that fix specific problems concerning safety hazards (e.g., potholes); preservation is usually proactive and scheduled in advance with periodic activities to slow down the deterioration of road pavements; pavement rehabilitation requires structural enhancements and is often triggered when it is necessary to extend the service life or upgrade the load carrying capacity of roads (Torres-Machi et al., 2018). Generally, these activities require materials, equipment use, and temporary road closure, thus having a crucial influence on the economic, social, and environmental aspects of the community. However, road agencies (e.g., Main Roads Western Australia) tend to make strategic maintenance plans for a road network based solely on pavement conditions and maintenance budget (Li, 2018). Because environmental effects are usually not considered as direct costs to road agencies and they do not have to pay for road user costs as they do for agency costs, most road agencies are reluctant to change their decision-making processes on road maintenance plans (Giustozzi et al., 2012).

The road design and maintenance plan can be assessed based on certain considerations. These may include direct costs, such as design fees, construction and future maintenance, road user costs, and other externalities, such as emissions and noise (Toole et al., 2007). The most commonly included assessment criterion is agency cost, including the direct cost of materials, equipment, and labor that will be included in the maintenance activities. Because agency cost has a direct impact on road agencies' financial performance, it is commonly adopted, along with pavement performance improvement to evaluate maintenance activities. Over the past few years, as an indicator to demonstrate the social impact of road maintenance, road user cost has been included in a few studies (France-Mensah and O'Brien, 2019; Gao and Zhang, 2013). However, the inclusion of road user cost remains challenging because of uncertainties (Beatty, 2002; Giustozzi et al., 2012). The reasons for this are that road user cost does not have a traded market value, and although a methodology to calculate road user cost has been developed, it is mainly used in the construction stage (Giustozzi et al., 2012). Given the increasing recognition of sustainability, environmental issues have now become a consideration as well, in both construction and infrastructure sectors (Wang et al., 2018). One of the most commonly adopted indicators in environmental assessment is greenhouse gas (GHG) emissions, which are considered significant contributors to global climate change (Wu et al., 2019). Based on these recent developments, it is imperative that the practices of evaluating maintenance decisions be improved from a cost-based approach to a sustainable one.

In recent years, researchers in the field of pavement management have begun taking these factors into consideration. For example, a sustainability evaluation framework that includes pavement performance, maintenance cost, and environmental consideration has been developed to evaluate the effectiveness of maintenance activities (Giustozzi et al., 2012). Similar indicators have also been considered by Ruiz and Guevara (2020) and Torres-Machi et al. (2017) to make decisions in formulating road preservation policies and selecting optimal road maintenance programs, respectively. However, it should be noted that these studies do not include road user cost, which represents the social impact of maintenance on a wider community. To integrate environmental and social sustainability indicators into the development of road maintenance treatments, Paik (2018) considered carbon emissions and road user cost in the decision making framework. Road conditions and agency cost, the most important indicators perceived by road agencies for making long-term maintenance decision making are not included, though. Recently, a sustainable pavement management plan that includes a tradeoff analysis of road conditions, road user costs, and greenhouse gas emissions has also been developed (France-Mensah and O'Brien, 2019). It should be noted that this framework was developed and tested for maintenance activities of road segments in a single year when maintenance activities are conducted. However, as road conditions continuously deteriorate and require constant maintenance over its period of use, life cycle costing analysis (LCCA), a method to evaluate an asset over its useful life cycle, should be used (Beatty, 2002). Salman et al. (2020) considered life cycle cost in their pavement maintenance selection framework, together with technical, environmental, and social considerations. However, the framework was developed for a single road segment. Compared with local governments and contractors who may focus on the performance of a single road segment, road agencies typically make maintenance plans to maximize the network performance. As such, for road agencies, pavement maintenance plans at a network level are expected to be more valuable. Existing studies are believed to have one or more of the following limitations: 1) few indicators beyond agency cost and road conditions are considered, meaning that environmental and social sustainability are often overlooked; 2) single road segment, instead of road network, is often investigated, which limits network-level decision making for road agencies; and 3) previous multi-attribute methods often rely on pre-determined importance levels for each indicator. However, road agencies may not always have an exact weight of each attribute, limiting the usability of the developed methods. As the selection of pavement maintenance plan can have long-time influence on the performance of road network, it is imperative that the decision making of road agencies is improved from cost-oriented to sustainability-oriented to achieve sustainable development.

This study therefore aims to: 1) develop a conceptual framework that is able to help select the optimal network-level pavement maintenance plan based on pavement conditions, maintenance costs, road user costs, and environmental considerations; and 2) demonstrate the use of a conceptual framework with network-level pavement maintenance plans. The expectation is that the proposed framework can be easily adapted and flexibly used by road agencies who would like to include sustainability into the decision making process. In addition, it is also expected to help road agencies select the network-level pavement maintenance plan that can achieve maximum sustainable benefits rather than mere economic benefits. The remainder of this paper is structured as follows. Section 2 presents a literature review related to the factors that can affect road maintenance decision-making. Section 3 discusses the method and framework. The results of the study and discussions thereof are presented in Section 4 and Section 5, respectively. Section 6 concludes this paper.

2. Literature review

The primary aim of road maintenance is to provide safe driving conditions and a uniform road surface, and to minimize the rate of deterioration of the pavement. To ensure the preservation of the asset and the convenience of road users, road maintenance focuses on activities related to the repair of defects in road structures and associated facilities (Veith and Bennett, 2006). The evaluation of road maintenance involves the consideration of many factors. The most common considerations are economic cost and pavement conditions (Torres-Machi et al., 2018). The economic cost of road maintenance is commonly recognized as agency cost in many studies (Pittenger et al., 2012). This can include materials, equipment, and labor usage in activities such as preventative maintenance, routine maintenance, and other rehabilitation or restoration activities (France-Mensah and O'Brien, 2019). The cost indicators, following the process of road pavement maintenance, include raw materials, mainly asphalt (which may include hot mix asphalt and warm mix asphalt), aggregate, sand, crushed brick/glass/concrete, and reclaimed asphalt pavement (RAP), if any, followed by the cost of mixing plant operations. When the mixed asphalt is produced, transportation and onsite placement are needed (Santos et al., 2017). Transportation equipment and onsite placement equipment, such as a bulldozer, compactor, dumper, and excavator, may be needed. Following the LCCA approach, which is commonly adopted in road design and construction evaluation, data on the agency cost can be obtained from historical records and current bids. If these data sources are not available, expert experience can be used to identify the agency cost.

Pavement conditions are among the most commonly adopted criteria for evaluating maintenance strategies. Pavement condition improvement after maintenance has been a dominant factor that influences road maintenance plans (Arif et al., 2016). Road agencies usually collect several road condition indexes (e.g., roughness, friction, rutting, cracking, and faulting) and then combine them to compute a single score to assess the quality of road pavements (Bektas et al., 2015). However, it is time-consuming and costly to monitor all these indexes constantly. Among these indicators, road roughness is a key factor related to the serviceability of a road (Al-Omari and Darter, 1994). In addition, road roughness usually decreases immediately after maintenance and increases as the road deteriorates. Therefore, road roughness is the most commonly used indicator to assess pavement performance when developing road pavement maintenance plans (France-Mensah and O'Brien, 2019). The international roughness index (IRI) is a standard index used to represent road roughness. The smaller the value of IRI, the smoother the pavement. Data on the IRI of roads before and after maintenance are often documented and updated by road agencies. There are also empirical formulas to estimate IRI values over time (Gao and Zhang, 2013).

Environmental aspects are attracting increasing consideration for the planning of pavement maintenance strategies for road networks, as many countries are evaluating the environmental sustainability of major projects (Giustozzi et al., 2012). GHG emissions are among the most important indicators. In road maintenance, the life-cycle emissions mainly come from the production and transportation of materials, onsite maintenance work, traffic delay, and fuel combustion due to rolling resistance. Traffic delay is usually caused by reduced speed along the work zone and/or road closure, which can lower road capacity (Huang et al., 2009). Reduced speed leads to decreases in fuel efficiency; thus, extra fuel is consumed, generating more emissions than normal use. When the road capacity of the work zone is lower than the traffic demand, vehicles will need to stop and queue or even detour over longer distances, generating more emissions. Rolling resistance is the result of the interaction between tires and the pavement when the engine keeps tires rolling on a pavement (Santos et al., 2015). Additional fuel will be combusted to overcome the rolling resistance of rough pavements (Trupia et al., 2017). To evaluate the life-cycle GHG emissions, process-based life cycle assessment (LCA) and environmental input output (EIO) LCA methods are usually adopted. As both methods have advantages and disadvantages, hybrid LCA methods have received increasing research interest recently (Crawford et al., 2018). As such, both EIO data and process data are needed to enable the evaluation. EIO data can often be obtained from government reports and relevant statistics. Process data such as the amount of materials and equipment use can be collected from material manufacturers and contractors. However, collecting first-hand data can be costly and time-intensive. In such cases, secondary data can be retrieved from the literature and authorized reports.

Social cost, or road user cost, is less frequently considered because of its complexity in calculation and the limited impacts on road agencies compared to agency costs (Giustozzi et al., 2012). Road user costs often include travel delay cost, vehicle operating cost (VOC), and crash cost (Batouli et al., 2017). Similar to traffic delay emissions, travel delay costs are generated because of traffic delays in the work zone. Owing to reduced speed, queueing, and/or detours, road users have to spend more time traveling through the work zone than usual. Their value of time is wasted. VOC often consists of fuel consumption, vehicle repair and maintenance, and tire wear. It can be affected by many factors such as traveling distance of vehicles, type of vehicles, traffic volume, traffic composition, pavement surface type, and pavement condition (Batouli et al., 2017; Chatti and Zaabar, 2012; Gao and Zhang, 2013). Generally, the rougher the pavement, the higher the VOC (Zaabar and Chatti, 2014). Moreover, crash cost can be impacted by many factors, such as crash rates and crash severity (Transport and Infrastructure Council, 2016). While there are several models and rich data available for the modeling of travel delay cost and VOC, data and existing models for crash cost are still scarce (Gao and Zhang, 2013). In addition, the relationships between maintenance treatment and accident rates are unclear (Giustozzi et al., 2012; Santos et al., 2017). Therefore, crash cost is often not considered in developing road pavement maintenance plans.

To combine multiple indicators in road maintenance planning, several methods have been adopted to achieve an optimal performance. One option is to consider Pareto optimization when there are no alternatives that can improve the results of one objective without compromising the performance of any other objectives (Wu et al., 2012). For example, Wei and Tighe (2004) developed a decision tree to integrate various technical and economic indicators to determine the most cost-effective preventive maintenance treatment. However, this study is cost-oriented and does not fully consider sustainability. To integrate road performance, cost, and environmental indicators for selecting optimal pavement maintenance plans, Yu et al. (2015) used genetic algorithms to generate a Pareto set and select the optimal solution from it. Salman et al. (2020) also adopted an analytic network process method to develop a road treatment selection framework. Technical performance and economic, environmental, and social sustainability were considered. However, it should be noted that these studies were all conducted at the project level, whereas road agencies often focus on the maintenance performance of the entire network. As such, Giustozzi et al. (2012) proposed a multi-attribute approach that can be implemented at the network level to combine environmental aspects with costs and road performance. A similar method was also used by Patidar (2007) to facilitate multi-objective optimization of investment at a network level based on technical performance, agency cost, and user cost considerations. As Wu et al. (2012) concluded, no single multi-objective decision making method is perfect for all factors such as user-friendliness, information or data availability, and cost for implementing the method. The multi-attribute decision-making approach is considered to be the best fit for this study, because it is suitable for use at the network level and road agencies' preferences can be quantified in the decision-making process (Wu et al., 2012).

3. Method

The framework proposed for evaluating a network-level pavement maintenance plan consists of four attributes, namely, road condition, economic, environmental, and social performance, as shown in Figure 1. The selection of criteria is based on France-Mensah and O'Brien (2019), which is one of the few studies that included environmental impacts and road user cost in developing a road management plan. Modifications have been made to ensure completeness and accuracy.

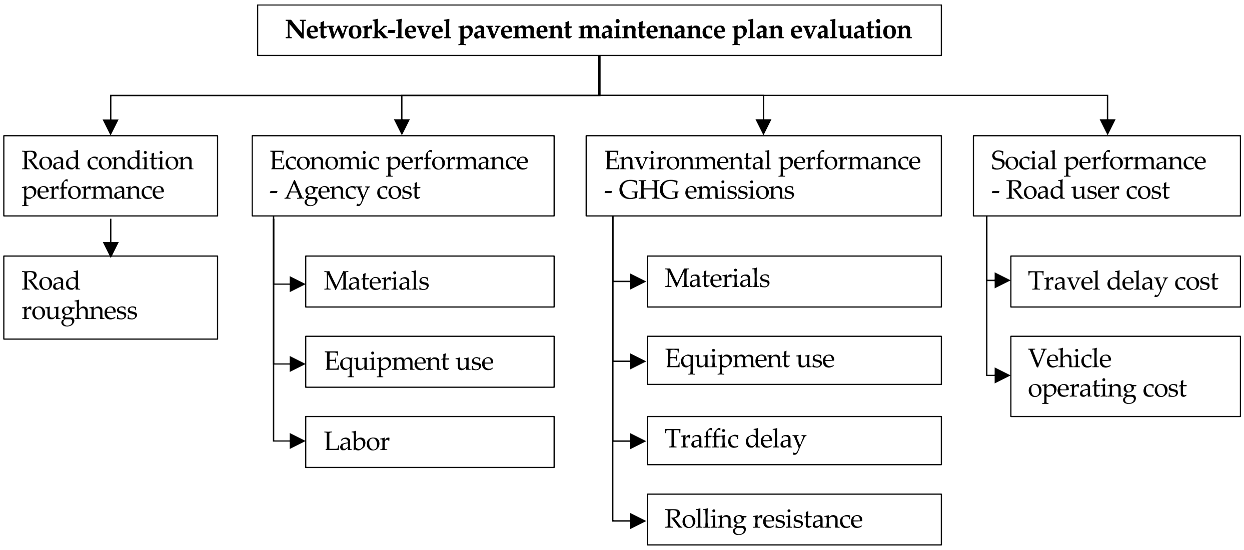

Figure 1. Framework for evaluating network-level pavement maintenance plan

France-Mensah and O'Brien (2019) included distress and roughness to assess road conditions. However, the distress score was developed for the Texas Department of Transportation and is difficult to apply in other countries or jurisdictions (France-Mensah and O'Brien, 2019). Investigating various factors requires numerous data and intensive time. In addition, combining different pavement performance factors into a single road condition indicator to enable multi-attribute decision making can be complex, and is beyond the scope of this study. According to Al-Omari (1994) and Gulen et al. (1994), road roughness (represented by IRI) is closely related to the serviceability of a road (represented by present serviceability index). Considering its international acceptance and wide use, road condition in this study is considered based on IRI as a measure of road roughness. This practice has also been supported by Yu et al. (2013) who used IRI to evaluate the serviceability of pavement when developing a methodology to select optimal maintenance strategies. Environmental performance is evaluated through a LCA of GHG emissions from materials, equipment use, traffic delay, and rolling resistance (France-Mensah and O'Brien, 2019). GHG emissions are targeted for two reasons. First, many countries (e.g., Australia, America, China) have committed to reducing GHG emissions (Jiang et al., 2020; The White House, 2015). Considering the large contribution of road transportation to GHG emissions, it is imperative to incorporate GHG emissions in the assessment of road maintenance plans (Climate Council, 2017). In addition, GHG emissions inventories are provided by many countries, making such data more accessible than those of other environmental impacts. Similar to France-Mensah and O'Brien (2019), road user costs, including travel delay cost and VOC, are calculated to evaluate social performance. Owing to the scarcity of models and data for crash cost and uncertain relationships between maintenance treatment and accident rates, crash cost is not included (Gao and Zhang, 2013; Giustozzi et al., 2012; Santos et al., 2017). It should be noted that the economic aspect is not included as one of the objectives of France-Mensah and O'Brien (2019). As the maintenance of pavement networks is long-term work, economic performance in this study is evaluated by life cycle agency cost, including materials, equipment, and labor use (Beatty, 2002). In addition, a multi-attribute decision-making approach adopted by Giustozzi et al. (2012) is used to combine the four attributes for an evaluation. The proposed framework is then validated using a case study.

3.1. Road condition

Road conditions were measured with IRI. A smaller value of IRI indicates lower roughness and better condition of the pavement. The road condition of the network was calculated using Eq. (1).

$$RC_t = \frac{\sum_{p=1}^{P} IRI_{pt} \times l_{pt}}{\sum_{p=1}^{P} l_{pt}} \tag{1}$$

where p is a single pavement segment of the road network under study and P indicates the number of pavement segments that form the network. Similarly, t is a single year of a studied time period (analysis period) and $t = 1$ is the first year in the analysis period. IRI_{pt} and l_{pt} represent the IRI and length of the pavement segment p in the tth year, respectively. RC_t is the pavement condition of the network in the tth year represented by the weighted average IRI of the entire network.

3.2. Agency cost

Agency costs usually include the direct cost of materials, equipment use, and labor. The agency cost (C_e) for the network-level pavement maintenance is calculated using Eq. (2).

$$C_e = \sum_{t=1}^{T}\sum_{p=1}^{P}(c_{mpt} + c_{ept} + c_{lpt})x_{pt} \quad (2)$$

where T refers to the analysis period. c_{mpt}, c_{ept}, and c_{lpt} represent the maintenance cost of materials, equipment use, and labor for pavement segment p in the tth year, respectively. c_{mpt}, c_{ept}, and c_{lpt} are calculated by multiplying the unit cost of the corresponding maintenance strategy by the treated area of the pavement being maintained. x_{pt} is a binary value of 1 or 0; 1 indicates that a maintenance strategy is allocated for pavement segment p in the tth year and 0 indicates that no maintenance is allocated. The network-level pavement maintenance plan for a period of 10 years (2017–2026) is obtained; thus, in this study, $T = 10$.

The plan indicates whether the pavement segment p receives a maintenance treatment in the tth year. For example, if the first pavement segment receives rehabilitation in 2018 during the analysis period, then $x_{1,2} = 1$ and $x_{1,t}$ $(t = 1,3,4,5,6,7,8,9,10) = 0$. $c_{m1,2}$, $c_{e1,2}$, and $c_{l1,2}$ represent the rehabilitation cost of materials, equipment use, and labor for this segment, respectively. As a result, the agency cost for the first pavement segment in this plan is $c_{m1,2} + c_{e1,2} + c_{l1,2}$. The details of the data sources and structure of the data are presented in Section 3.6.

The present cost method is adopted in this study, which discounts the yearly cost to an equivalent cost that occurs at the beginning of the analysis period. The results are presented in the form of net present value (NPV). In addition, an equivalent uniform annual cost method is also adopted to obtain an equivalent annual cost for a network-level pavement maintenance plan. For this purpose, the net annual value (NAV) is calculated. A discount rate of 4% was adopted in accordance with previous studies (Giustozzi et al., 2012) and a discussion with a local road agency.

3.3. Greenhouse gas emissions

LCA was used to evaluate the GHG emissions of the road network. The functional unit is the entire road network, and the maintenance and use phases are considered as the system boundary.

Specifically, embedded emissions from materials extraction and production, onsite equipment operation and traffic delay due to maintenance work are included in the maintenance phase. The use phase considers rolling resistance effect because of its relatively high impact and well-established evaluation methods (Santero and Horvath, 2009). The analysis period is 10 years, which is the same as that of the agency cost analysis. GHG emissions of the road network (E_c) are calculated by summing the network emissions from materials and equipment use (E_{me}), traffic delay during maintenance (E_{td}), and rolling resistance (E_{rr}), as shown in Eq.(3a) (France-Mensah and O'Brien, 2019).

$$E_c = E_{me} + E_{td} + E_{rr} \tag{3a}$$

The network GHG emissions from materials and equipment are calculated by summing the emissions from each road segment, as demonstrated by Eq. (3b).

$$E_{me} = \sum_{t=1}^{T} \sum_{p=1}^{P} (e_{mept}) x_{pt} \tag{3b}$$

where e_{mept} represents GHG emissions from materials and equipment use of a pavement segment p in the tth year. Specifically, e_{mept} was calculated through a path exchange (PXC) hybrid LCA method (Jiang et al., 2020). This method follows four steps, including building an EIO LCA model first, extracting the most carbon intensive nodes, deriving case-specific data and using case-specific data to substitute the identified nodes that have the highest emissions in the EIO LCA model (Treloar et al., 2004). This method is adopted because it avoids the cut-off errors of the traditional process-based LCA method while still having an adequate level of accuracy without double counting (Crawford et al., 2018). Detailed information for this calculation can be found in Jiang et al. (2020).

For emissions from traffic delay and rolling resistance, it is difficult to fit the fuel use into an economic sector. Therefore, the PXC method is not applicable, and a tiered hybrid LCA method is used (Jiang et al., 2020). The first step is to obtain process-based data (i.e., direct fuel combustion) and EIO data are then derived for all other upstream processes such as raw material extraction and fuel production (Wang et al., 2012). The network GHG emissions from the traffic delay and rolling resistance are calculated using Eq. (3c) and Eq. (3d), respectively.

$$E_{td} = \sum_{t=1}^{T} \sum_{p=1}^{P} (e_{tdpt}) x_{pt} \tag{3c}$$

$$E_{rr} = \sum_{t=1}^{T} \sum_{p=1}^{P} e_{rrpt} \tag{3d}$$

where e_{tdpt} and e_{rrpt} represent the GHG emissions from the traffic delay and rolling resistance of a pavement segment p in the tth year, respectively. During traffic delay, GHG emissions are generated from three main sources, including vehicles queueing in line, getting through the work zone at a lower speed, and taking a detour (Jiang et al., 2020; Yu and Lu, 2012). These emissions in total are higher than vehicle emissions from normal road use and such increase is attributed to road maintenance. Therefore, e_{tdpt} can be calculated through Eq. (3e) (Yu and Lu 2012).

$$e_{tdpt} = (e_{queue} + e_{workzone} + e_{detour} - e_{normal})_{pt} \tag{3e}$$

where e_{queue}, $e_{workzone}$, e_{detour} and e_{normal} stand for GHG emissions generated from vehicles queueing in line, traveling through the maintenance work zone at a lower speed, taking a detour, and getting through the work zone at a normal speed respectively.

Rolling resistance effect, on the other hand, measures GHG emissions generated from fuel combustion due to interaction of vehicle tires and uneven road pavement. Such interaction can be affected by vehicle speed and pavement features such as roughness (represented by IRI) and macrotexture (represented by mean profile depth, MPD). As cars and trucks have different interaction mode, the fuel use is calculated separately. Therefore, e_{rrpt} is calculated through Eq. (3f) - (3h) (Hammarström et al. 2012).

$$e_{rrpt} = \left(\frac{f_{cpt} \times AADT_{pt} \times Perc_{cp} \times ef_c}{v_{cp}} + \frac{f_{trpt} \times AADT_{pt} \times Perc_{trp} \times ef_{tr}}{v_{trp}}\right) \times l_p \times 365 \tag{3f}$$

$$f_{cpt} = 0.103(1.208 + 0.000479 \times IRI_{pt} \times v_{cp} + 0.0393 \times MPD_{pt})^{1.163} \times v_{cp}{}^{1.056} \tag{3g}$$

$$f_{trpt} = 0.246(1.451 + 0.00172 \times IRI_{pt} \times v_{trp} + 0.111 \times MPD_{pt})^{1.027} \times v_{trp}{}^{0.960} \tag{3h}$$

where f_{cpt} (f_{trpt}) represents the fuel use of a single car (truck) per hour due to its rolling resistance on pavement p in the tth year. $AADT_{pt}$, IRI_{pt}, and MPD_{pt} are annual average daily traffic (AADT), IRI, and MPD of pavement segment p in the tth year. $Perc_{cp}$ ($Perc_{trp}$), l_p, and v_{cp} (v_{trp}) refer to percentage of cars (trucks), road length, and the traveling speed of cars (trucks) on pavement p. ef_c (ef_{tr}) means emission factors for car (truck) fuel. Gasoline and diesel fuel are considered as typical fuel for cars and trucks, respectively (Oak Ridge National Laboratory, 2020).

Finally, to assess the environmental impact of the emissions, the global warming potential (GWP) was selected as the characterization factor. All GHG emissions, including carbon dioxide, methane, nitrous oxide, hydrofluorocarbons, perfluorocarbons, and sulfur hexafluoride, are converted to carbon dioxide equivalents (CO_2-e).

3.4. Road user cost

The travel delay cost (C_{td}) and VOC (C_{voc}) are considered in this study to calculate the road user cost (C_s), as indicated by Eq. (4a).

$$C_s = C_{td} + C_{voc} \tag{4a}$$

As shown in Eq. (4b), the calculation of travel delay cost is similar to that of traffic delay emissions.

$$C_{td} = \sum_{t=1}^{T} \sum_{p=1}^{P} (c_{queue} + c_{workzone} + c_{detour} - c_{normal})_{pt} x_{pt} \tag{4b}$$

where c_{queue}, $c_{workzone}$, c_{detour}, and c_{normal} represent the fuel cost generated from vehicles queueing in line, traveling through the maintenance work zone at a lower speed, taking a detour, and getting through the work zone at a normal speed, respectively.

VOC consists of fuel cost (C_f), repair and maintenance cost (C_{rm}), and tire wear cost (C_{tw}) (Zaabar and Chatti, 2014). As roads deteriorate and IRI increases, vehicle fuel use and its cost, repair and maintenance cost, and tire wear cost all rise as a result (Liu et al., 2020). Therefore, the VOC must be adjusted according to the change in IRI during the analysis period. Eq. (4c)–(4e) were used for the calculation.

$$C_f = \sum_{t=1}^{T} \sum_{p=1}^{P} (c_{normal})_{pt} \times C_{1pt} \times (IRR_{pt} - IRR_0) \tag{4c}$$

$$C_{rm} = \sum_{t=1}^{T} \sum_{p=1}^{P} (c_{rm})_{pt} \times C_{2pt} \times (IRR_{pt} - IRR_0) \quad (4d)$$

$$C_{tw} = \sum_{t=1}^{T} \sum_{p=1}^{P} (c_{tw})_{pt} \times C_{3pt} \times (IRR_{pt} - IRR_0) \quad (4e)$$

where C_{npt} $(n = 1, 2, 3)$ is a coefficient that represents the change in fuel cost $(n = 1)$, repair and maintenance cost $(n = 2)$, and tire wear cost $(n = 3)$ per m/km change in IRR. The coefficients were adapted from Zaabar and Chatti (2014). IRR_0 represents the baseline value of IRI, which equals 1 (Zaabar and Chatti, 2014). $(c_{rm})_{pt}$ and $(c_{tw})_{pt}$ are the repair and maintenance cost and tire wear cost for the pavement segment p in the tth year, respectively. The details of the data and data sources are presented in Section 3.6. Similar to the agency cost, the social cost is also discounted to NPV and NAV at a discount rate of 4%.

3.5. Multi-attribute decision making approach

Multi-attribute decision-making concerns making decisions among a set of finite alternatives that typically conflict with each other (Triantaphyllou and Baig, 2005). Three steps are needed in a multi-attribute decision-making approach. The first is assigning weights to each attribute to determine the importance of the attributes, where a higher weight indicates a higher importance. The weights can vary according to the preference of the decision makers. The second step is the normalization or rescaling of the attribute values of the alternatives to enable a comparison. The values of an attribute should be normalized to the range of 0 to 1, with 1 representing the highest value. The last step is to combine all the attributes into a single index to inform decision making. Various methods such as the weighted sum model (WSM) and analytic hierarchy process method are available. It is difficult, if at all possible, to know which method provides the "correct" answer, but the WSM method is the most widely adopted, possibly because of its ease of use (Triantaphyllou and Baig, 2005; Yang, 2020). Therefore, this study adopts the following three steps:

1) Assigning initial weights for road condition, agency cost, GHG emissions, and road user cost.

2) Normalizing the attribute values of alternative maintenance plans to fit in the range of 0 to 1. The highest value of each attribute is rescaled to 1, and the values of other alternatives are rescaled proportionally according to Eq. (5a) (Giustozzi et al., 2012).

3) Combining the normalized values of the four attributes into a single value for every maintenance plan using the WSM method. Eq. (5b) and (5c) were used for the calculation (Triantaphyllou and Baig, 2005).

$$x_{ij} = \frac{a_{ij}}{a_{max,j}} \times 1 \tag{5a}$$

$$P_i = \sum_{j=1}^{n} a_{ij} \times w_j \tag{5b}$$

with $$\sum_{j=1}^{n} w_j = 1,\ w_j > 0 \tag{5c}$$

where i indicates an alternative maintenance plan for the pavement network. j denotes an attribute, and n is the total number of attributes, namely 4 in this study. a_{ij} represents the performance of the alternative plan i in terms of attribute j and $a_{max,j}$ is the highest value among all the alternatives for attribute j. P_i is the WSM value for the maintenance plan i. In addition, w_j refers to the nonnegative weight of attribute j. Equal weights are adopted as an example to illustrate the application of the proposed framework. As such, w_j equals 0.25 for all four attributes. As different road agencies have their own preferred importance ranking of the four attributes, 1000 sets of weights are then randomly generated for the four attributes to cover wider preferences, according to Yang (2020). First, four numbers u_j that follow a normal distribution N (0,1) are generated, assuming that most decision-makers do not have extreme preferences. Then, the four numbers are normalized according to Eq. (5d), such that Eq. (5c) is satisfied. Finally, the first two steps are repeated 1000 times. The WSM method with random weights has been proven to work well (Yang, 2020).

$$w_j = \frac{u_j}{\sum_{j=1}^{4} u_j} \tag{5d}$$

As a result, the generated weights for road conditions, economic, environmental, and social aspects have ranges of 0.0008–0.7790, 0.0002–0.8040, 0.0002–0.8605, and 0.0005–0.8898, respectively. This should cover most of the preferences of decision-makers, including certain extreme situations, such as when the environmental aspect receives higher significance due to aggressive emissions reduction targets.

3.6 Case study

The proposed framework is demonstrated with eight network-level pavement maintenance plans. The road network consists of 16,539 road segments in Western Australia, which extend 17,299.28 km. Most of the road segments (71.9%) are granular, and 28.1% have asphalt pavements. Medium standard single carriageway is the most common road classification, accounting for 39.1%, followed by heavy traffic roads (generally in metropolitan area) which make up 18.9%. High standard and basic standard single carriageways account for 16.5% and 14.0% respectively and the others are freeways (11.5%). Among these road segments, 88.8% have two lanes. The lane width of the entire network ranges from 3.4m to 42.5m, with an average of 9.2m and a standard deviation of 2.6m. The average initial IRI of the network is 2.6104, ranging from 0.3333 to 8.2200 with a standard deviation of 0.7460. The AADT of the network in the first year of the analysis period (2017–2026) ranges from 43 to 101,259 with an average of 6,534 vehicles per day. The annual traffic growth rate was assumed to be 2%. In addition, over half of the road segments have limited the vehicle speed within 110km/h and the average percentage of heavy trucks was 25.7%.

There are eight maintenance and rehabilitation (M&R) strategies to be considered for each road segment, as shown in Table 1. The definitions of these strategies were obtained from Main Roads Western Australia (Main Roads), a road agency in Western Australia. Among these strategies, structural rehabilitation strategy for asphalt pavements (ASRS) and granular overlay (GrOL) are rehabilitation strategies that cost more but perform better in improving the IRI of pavements. Others require only regular maintenance, and the improvement in road conditions is relatively limited. One or zero of these M&R strategies is triggered for each road segment of the studied road network every year, depending on its condition and the maintenance budget of the entire network. Eight network-level maintenance plans with different budgets (budget scenarios) are considered by Main Roads, namely AUD$50 million (50M), AUD$60 million (60M), AUD$70 million (70M), AUD$85 million (85M), AUD$95 million (95M), AUD$105 million (105M), AUD$115 million (115M), and AUD$125 million (125M). The value corresponds to an approximate value related to the yearly routine maintenance budget. The 50M and 125M budget scenarios are demonstrated as examples in Tables S1 and S2, specifying when, where, and what M&R strategy to apply in a road network under a certain budget scenario. The algorithm behind the allocation is explained in Li (2018). Generally, rehabilitation strategies are more frequently triggered under a scenario with a higher budget. When the maintenance budget is insufficient, nonrehabilitation strategies are triggered until road conditions deteriorate to a certain standard.

Table 1 Eight maintenance and rehabilitation (M&R) strategies considered in the case study demonstration

M&R programs	Descriptions
ASDG	Dense graded asphalt replacement (Asphalt mixing plant, paver and compactor) (30 mm)
ASIM	Intersection mix asphalt replacement (Asphalt mixing plant, paver and compactor) (40 mm)
ASOG	Open graded asphalt replacement (Asphalt mixing plant, paver and compactor) (30 mm)
ASRS	Full depth asphalt (Major rehabilitation - replacing the top 150 mm and 5% of road to full depth. The rehabilitation takes place every 50 years)
CS	Surface dressing: spraying a layer of bitumen on the road surface and laying one or more layers of aggregates
Slurry	Cold mixed surface treatments, including application of 3–20 mm in-situ mixture of aggregate, cement/lime, polymer modified bitumen emulsion, adhesive, and water
RipSeal	50 mm gravel replacement with cement stabilization and seal
GrOL	Major rehabilitation. Replacing 150 mm of aggregates with cement stabilization and seal

(Reference: Wu et al., 2017).

Network-level pavement maintenance plans under the eight budget scenarios were provided by Main Roads. All other data sources are summarized in Table 2.

Table 2 Data demands and data sources for the four attributes

Attributes		**Data demands**	**Data sources**
Road condition		IRI of each road segment, pavement length	Main roads, predicted by dTIMS V9 of Deighton (Li, 2018)
Economic performance (Agency cost)		Unit rate of each M&R strategy, treated area	Main roads
Environmental performance (Greenhouse gas emissions)	PXC model	Direct requirement coefficients matrix	Australian National Accounts (ABS, 2018)
		Australian greenhouse gas inventory	Australian Government (2019)
		Output of each economic sector	IBISWorld (2019)
		Material and equipment use for each maintenance strategy	Main roads
	Tiered hybrid model	Queue speed	Assume to be 8 km/h
		Queue length	Calculated through obtained data
		Work zone	Department of Infrastructure (2015)
		Detour speed, detour distance	60km/h (Santos et al., 2015), 10km (Chen et al., 2016)
		Fuel efficiency at a specific speed	Oak Ridge National Laboratory (2019)
		Road and traffic information (e.g., IRI, pavement length, MPD, AADT, traffic composition, speed limit)	Main roads
		Emission factors	TAGG (2013)
Social performance (Road user costs)	Travel delay cost	Travel delay time	Calculated through obtained data
		Value of time (Value per occupant×occupancy rate)	Cars (\$/veh-hour): (37.46×5/7+14.99×2/7)×1.245; trucks (\$/veh-hour): 16.81×1.0 (Transport and Infrastructure Council, 2016)
	VOC	Fuel price	Car fuel: 1.470\$/L; truck fuel: 1.596\$/L (Transport and Infrastructure Council, 2016)
		Parameters for vehicle repair and maintenance	Cars: 6.3 cents/km; trucks: 14.0 cents/km (Transport and Infrastructure Council, 2016)
		Tire wear parameters	Cars: 492\$/set of tires; trucks: 6618\$/set of tires. Assuming per set of tire can last 40000km (Transport and Infrastructure Council, 2016)

4. Results

4.1. Road condition

Figure 2 presents the yearly average IRI of the network. It can be observed that all maintenance budget scenarios have the same initial IRI. As time passes, pavements deteriorate and IRI increases instantly. In addition, the rate of increase varies for different scenarios. It is obvious that the increase in the IRI is much slower when the maintenance budget increases. This indicates that a higher budget can lead to better improvement in road conditions. The reason for this is that more road segments will receive M&R treatment when more maintenance funds are available. For example, an average of 6.76% of road segments is maintained under the 50M scenario, and this value gradually increases to 7.13% under the 125M scenario.

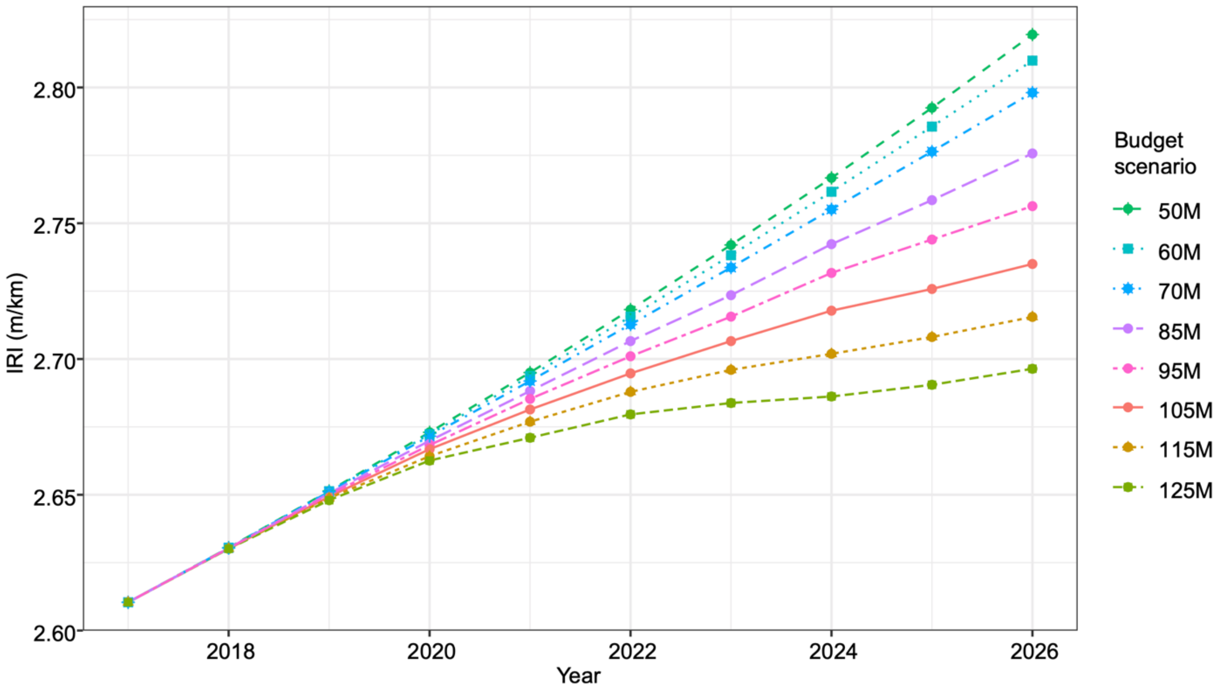

Figure 2. Average IRI of the road network

4.2. Agency cost

The yearly agency costs for each maintenance budget scenario are presented in Table 3. The total cost for the network-level M&R during 2017–2026 is equivalent to AUD$946.417–AUD$1,036.660 million, depending on the budget. In addition, it is interesting to find that the equivalent annual costs of all options are above AUD$115 million. Specifically, in 2026, the agency cost increases sharply, especially under scenarios 50M, 60M, and 70M. The lower the budget, the sharper the increase. Owing to the relatively lower annual routine maintenance budget in earlier years, more rehabilitation work is needed in 2026.

To this end, a further analysis on the percentage of road segments that receive M&R each year is conducted. Under the 50M, 60M, and 70M scenarios, road segments receiving M&R account for an average of 5.2%, 5.8%, and 6.4%, respectively, from 2017 to 2025 and 21%, 15.5%, and 11.3%, respectively, in 2026. Specifically, under these three scenarios, an average of 2.0%, 1.9%, and 2.2% receive rehabilitation in 2017–2025, and 8.5%, 8.6%, and 9.6% receive rehabilitation in 2026. Under the 85M, 95M, and 105M scenarios, it should be noted that the percentage of road segments receiving M&R in 2017–2026 does not change much, but the percentage of segments receiving rehabilitation in 2026 is significantly higher than that in previous years, increasing from 2.3% to 9.3%, 2.6% to 7.7%, and 2.8% to 5.3%, respectively. For the 115M and 125M scenarios, a large number of maintenance activities happen every year across the 10-year period, and there is no observed sharp increase in 2026.

The NAV per kilometer is also calculated, and Figure 3 visualizes the difference between the eight maintenance budget scenarios. It can be seen from the figure that scenario 85M has the lowest agency cost. The NAV is AUD$6,745.06/km. Interestingly, the 50M scenario turns out to be the most expensive in the long term, costing an equivalent of AUD$7,388.22/km per year.

Table 3 Agency cost for the eight maintenance budget scenarios (unit: AUD$M)

Scenario	2017	2018	2019	2020	2021	2022	2023	2024	2025	2026	NPV	NAV
50M	53.228	52.261	50.929	50.465	48.596	50.750	46.218	45.921	46.537	928.784	1036.660	127.811
60M	63.777	61.593	59.861	60.291	58.310	60.028	56.144	57.044	54.152	793.472	1015.898	125.251
70M	73.701	71.596	68.836	71.191	67.383	69.079	67.350	64.551	61.567	651.974	989.188	121.958
85M	89.984	84.499	85.614	81.994	84.830	82.700	81.702	80.108	77.120	428.208	946.417	116.685
95M	100.058	94.065	94.577	93.474	91.296	98.122	93.867	87.886	84.574	324.184	950.270	117.160
105M	109.475	105.712	103.415	101.388	105.275	106.966	100.422	92.855	93.479	244.045	964.470	118.910
115M	119.631	116.607	108.992	113.313	115.090	115.025	106.497	100.317	100.825	190.541	994.121	122.566
125M	129.218	126.042	119.883	123.185	123.338	121.320	105.541	108.146	109.776	134.751	1016.387	125.311

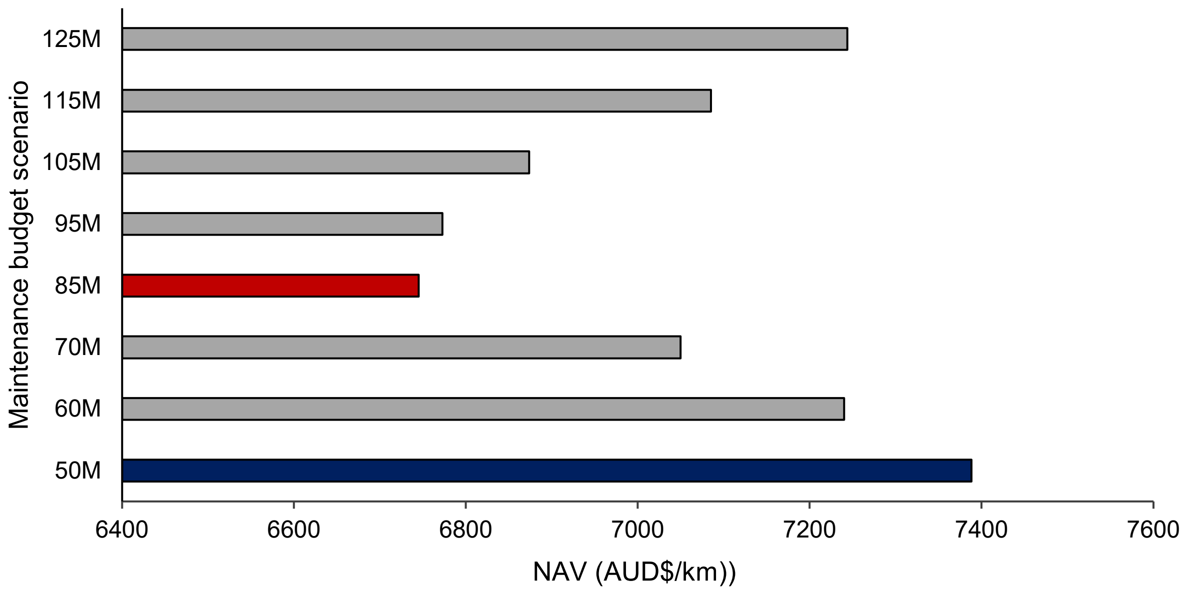

Figure 3. Unit agency cost of the eight maintenance budget scenarios

4.3. Greenhouse gas emissions

The results of the network emissions under the eight maintenance budget scenarios are presented in Table 4. It was found that an average of at least 8.9900 million tCO_2-e emissions are generated per year. The use phase has a dominant role and contributes an average of 99.2% to the total emissions, regardless of the budget. The emissions from the use phase could be impacted by AADT, IRI, MPD, and the speed limit. A sensitivity analysis was conducted to evaluate the impact of these factors on emissions. The results show that the variation in the emissions due to the change in AADT may be up to 99.9%, which is much higher than that of other factors. In addition, the average GHG emissions of the road network increase slightly every year for all maintenance budget scenarios. This could have resulted from the annual growth of AADT.

Compared with the use phase, the contribution of the maintenance phase is negligible, especially in the first nine years. In 2017–2025, the average contribution of the maintenance phase under scenario 50M is 0.30%. With the increase in maintenance budget, this value gradually increases to 0.78% under scenario 125M. On the contrary, in 2026, the maintenance phase accounts for 5.07% of total GHG emissions under scenario 50M, and this percentage decreases to 0.76% under scenario 125M. This finding is similar to the previous finding on the distribution of agency costs. In 2026, network-level maintenance plans with lower budgets generate higher emissions owing to the large number of maintenance activities and a high percentage of rehabilitation programs.

Table 4 GHG emissions of the network under the eight maintenance budget scenarios (unit: million tCO_2-e)

Scenario	2017	2018	2019	2020	2021	2022	2023	2024	2025	2026	Average
50M	8.165	8.331	8.500	8.671	8.847	9.030	9.211	9.396	9.588	10.274	9.0013
60M	8.170	8.336	8.505	8.679	8.854	9.037	9.218	9.404	9.590	10.196	8.9989
70M	8.174	8.342	8.512	8.686	8.861	9.043	9.227	9.410	9.594	10.110	8.9960
85M	8.182	8.350	8.524	8.696	8.872	9.053	9.235	9.419	9.603	9.980	8.9914
95M	8.187	8.357	8.530	8.703	8.877	9.062	9.245	9.421	9.604	9.918	8.9904
105M	8.192	8.365	8.538	8.708	8.885	9.068	9.246	9.419	9.606	9.874	8.9900
115M	8.197	8.372	8.543	8.714	8.891	9.069	9.245	9.420	9.609	9.846	8.9906
125M	8.202	8.380	8.549	8.720	8.894	9.071	9.240	9.423	9.612	9.818	8.9909

Figure 4 presents the distribution of unit GHG emissions under the eight maintenance budget scenarios. It shows that the unit GHG emissions of scenarios 85M-125M are very close, varying from 519.68 t CO_2-e/km (105M) to 519.76 t CO_2-e/km (85M). Scenarios 50M, 60M, and 70M have much higher unit GHG emissions. The 50M scenario has the highest emissions of 520.33 t CO_2-e/km. The main reason for the close results could be that IRIs with different maintenance budget do not vary much from each other under network-level consideration. The percentage of road segments that receives maintenance treatments is low regardless of the budget, at an average of approximately 7% each year.

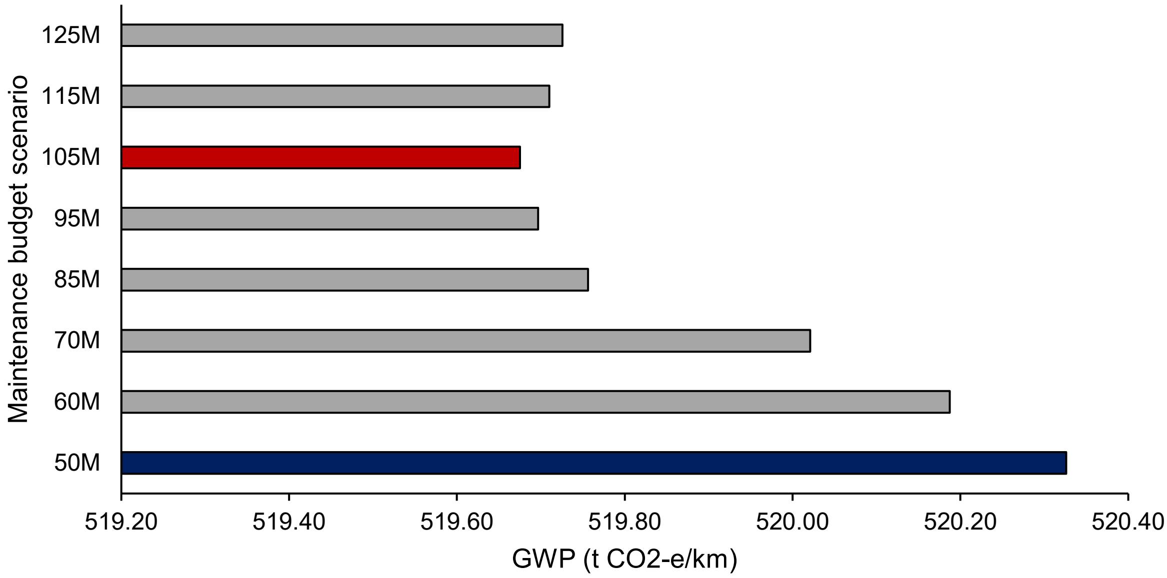

Figure 4. Unit GHG emissions of the eight maintenance budget scenarios

4.4. Road user cost

Table 5 shows the road user costs for the eight maintenance budget scenarios. It can be seen from the table that an equivalent of AUD$28.205–28.257 billion is spent by road users across the entire network during 2017–2026. That is, an equivalent of AUD$3,477.369–3,483.875 million of road user cost is spent annually owing to travel delay and vehicle operation (i.e., fuel use, repair and maintenance of vehicles, and tire wear). This is more than 27 times the agency cost. Fuel cost is the most significant contributor to the total social cost, accounting for approximately 43.1%. Repair and maintenance costs and tire wear costs also contribute approximately 38.7% and 18.2%, respectively. On the contrary, travel delay cost only contributes less than 0.1% to the total social cost due to the limited duration of maintenance work compared to the continuous vehicle operation in a certain year.

A constant increase in road user cost from 2017 to 2026 is observed for all maintenance budget scenarios. The annual increase rate for each scenario ranges from 2.00% to 2.06%, with an average of 2.03%. As the contribution of travel delay cost is negligible, this could possibly be impacted by AADT and IRI, which generally tend to increase over time. In order to identify which factor is most important, the user cost per vehicle per kilometer traveled is calculated, such that only IRI has an impact. As shown in Table 6, each vehicle traveling 1 km costs approximately AUD$89 per year and the highest average annual increase rate among all the maintenance budget scenarios is 0.13%, which is significantly lower than 2.03%. This indicates that AADT has a more significant impact on the road user cost of the entire network. Moreover, it is also observed that the road user cost (both network NAV and NAV per vehicle per kilometer) slowly decreases as the maintenance budget increases from 50M to 125M. This is possibly because the IRI of pavements is improved with a higher budget.

4.5 Multi-attribute decision making

Because the 50M scenario has the highest value for all four attributes, it is rescaled to have a maximum value of 1. The other scenarios are rescaled using Eq. (5a), and the weighted sum values are obtained through Eq. (5b). The rescaled and WSM results with equal weights for the eight maintenance budget scenarios are shown in Table 7. The lower values indicate better performance. It can be seen that the rescaled values for road condition, economic, environmental, and social considerations range from 0.9837 to 1, 0.9129 to 1, 0.9987 to 1, and 0.9970 to 1, respectively. This is because the variation in economic performance among the eight scenarios is much higher than that in other attributes. In addition, it can be inferred that scenarios with high economic performance (low economic values) are more likely to generate low WSM values.

Table 5 Road user cost of the network under the eight maintenance budget scenarios (unit: AUD$M)

Scenario	2017	2018	2019	2020	2021	2022	2023	2024	2025	2026	NPV	NAV
50M	3072.678	3135.301	3199.277	3264.165	3331.227	3399.022	3469.368	3541.569	3615.174	3692.288	28257.347	3483.875
60M	3072.895	3135.282	3199.014	3263.534	3330.349	3398.121	3468.556	3540.672	3614.359	3690.323	28251.951	3483.210
70M	3073.061	3135.278	3198.606	3263.124	3329.589	3397.624	3467.485	3539.373	3613.061	3688.121	28245.984	3482.474
85M	3073.334	3135.192	3197.937	3262.465	3328.707	3396.125	3465.567	3537.281	3610.778	3684.697	28235.804	3481.219
95M	3073.546	3135.061	3197.714	3261.946	3328.046	3395.120	3464.660	3536.010	3609.119	3682.019	28229.055	3480.387
105M	3073.678	3135.020	3197.342	3261.714	3327.299	3394.158	3463.279	3534.083	3606.698	3679.068	28220.768	3479.365
115M	3073.827	3134.898	3197.150	3261.064	3326.507	3393.260	3461.752	3532.141	3604.082	3676.329	28212.111	3478.298
125M	3073.949	3134.693	3196.967	3260.695	3325.641	3391.984	3460.204	3530.579	3602.253	3674.299	28204.577	3477.369

Table 6 Annual road user cost per vehicle per km of the eight maintenance budget scenarios (unit: AUD$/km·vehicle)

Scenario	2017	2018	2019	2020	2021	2022	2023	2024	2025	2026	NAV
50M	85.498	85.581	85.670	85.757	85.853	85.947	86.068	86.189	86.329	86.541	89.344
60M	85.498	85.582	85.670	85.755	85.847	85.935	86.042	86.158	86.288	86.478	89.328
70M	85.499	85.582	85.670	85.752	85.838	85.922	86.020	86.120	86.238	86.398	89.308
85M	85.500	85.583	85.669	85.745	85.819	85.887	85.965	86.047	86.137	86.239	89.267
95M	85.500	85.584	85.667	85.738	85.807	85.858	85.923	85.985	86.044	86.108	89.232
105M	85.500	85.585	85.665	85.730	85.784	85.815	85.850	85.886	85.900	85.922	89.179
115M	85.501	85.586	85.663	85.714	85.757	85.771	85.786	85.775	85.766	85.787	89.129
125M	85.502	85.586	85.661	85.705	85.711	85.713	85.691	85.651	85.639	85.645	89.073

Table 7 Rescaled and WSM results for the eight maintenance budget scenarios

Scenario	Road roughness	Economic cost	Environmental impact	Social cost	Weighted sum
50M	1.0000	1.0000	1.0000	1.0000	1.0000
60M	0.9989	0.9800	0.9997	0.9998	0.9946
70M	0.9975	0.9542	0.9994	0.9996	0.9877
85M	0.9947	0.9129	0.9989	0.9991	0.9764
95M	0.9924	0.9167	0.9988	0.9987	0.9766
105M	0.9896	0.9304	0.9987	0.9981	0.9792
115M	0.9867	0.9590	0.9988	0.9976	0.9855
125M	0.9837	0.9804	0.9988	0.9970	0.9900

To provide an intuitive comparison of the various maintenance budget scenarios, Figure 5 presents the WSM results. It is evident that the 85M scenario has the lowest WSM value, indicating that it is the optimal alternative.

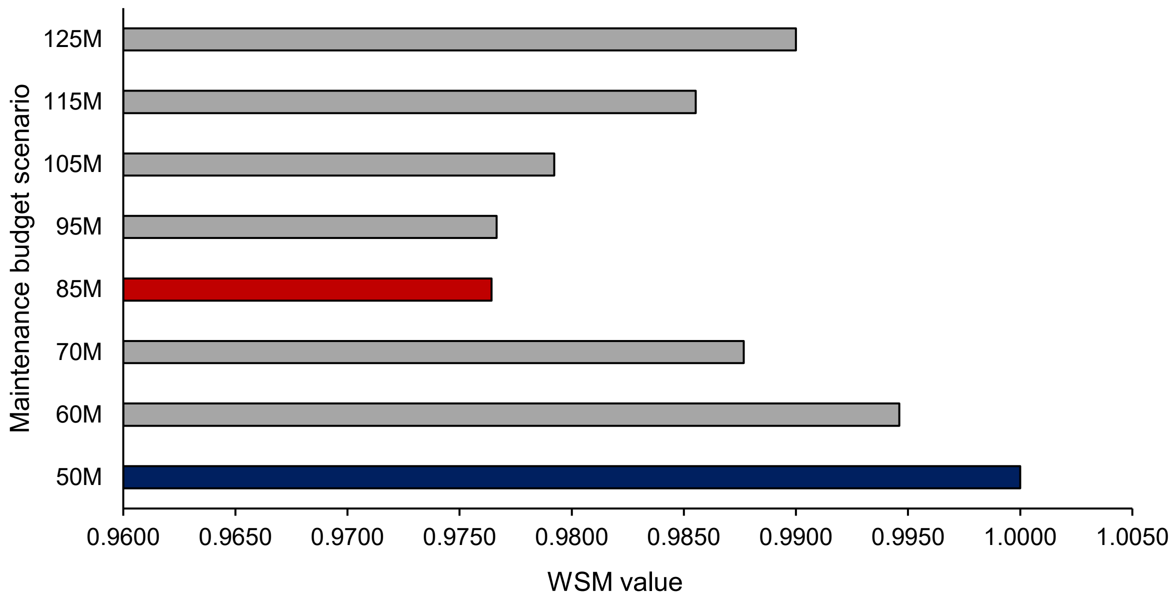

Figure 5. WSM results for the eight maintenance budget scenarios

The results for the 1000 random runs are presented in Figure 6. It is obvious that scenarios 85M, 95M, 125M, and 105M generally have relatively low WSM results. Among the 1000 random draws, the 85M scenario is selected as the optimal option 596 times, accounting for 59.6%. The 95M, 125M, and 105M scenarios account for 26.6%, 7.7%, and 6.1%, respectively. Although the 125M scenario has relatively high WSM values in the 1000 runs, it can be an optimal option under several conditions, for example, when the maintenance budget is sufficient and the economic aspect is given very low weight (e.g., < 6%).

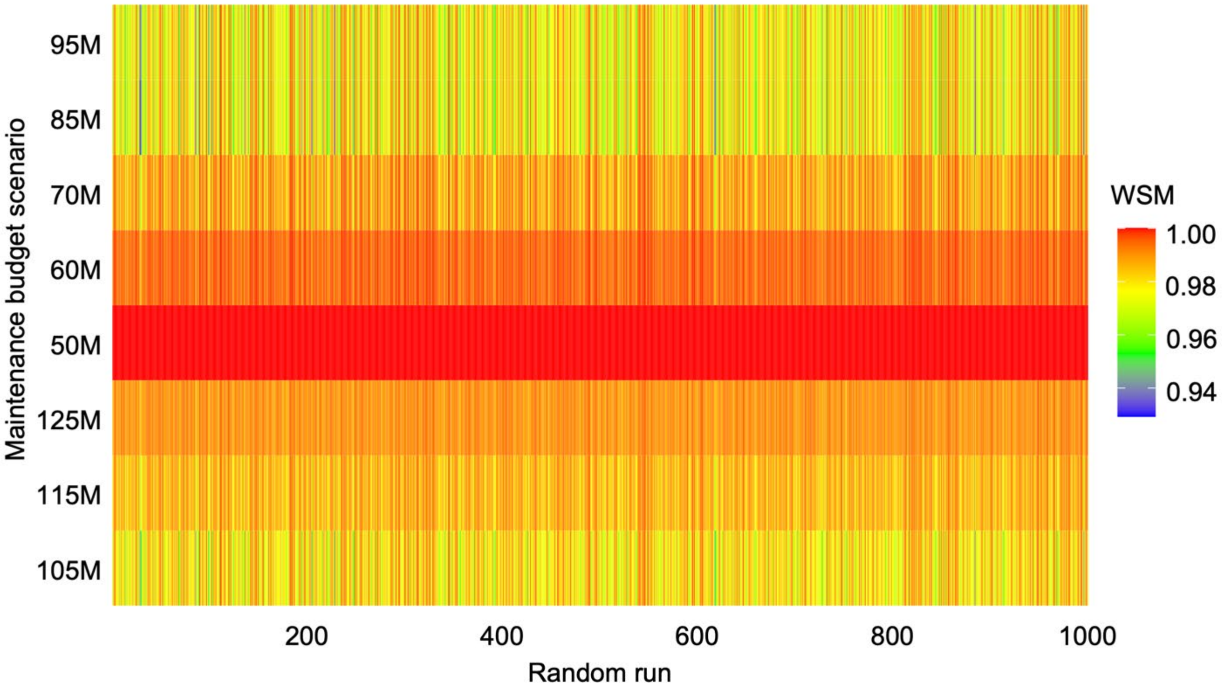

Figure 6. WSM results for the 1000 random runs

Furthermore, Figure 7 shows the relationships between the four potential optimal scenarios and the allocated weights of the four attributes. The darker circles indicate that the respective scenarios are selected more frequently. It can be observed that the optimal results are sensitive to the weight of economic considerations. When the weight is extremely low (e.g., < 2%), only scenario 125M will be selected and scenario 85M will not be selected until the weight is higher than 8%. In addition, when economic considerations account for 27% of the overall weight, the possibility that scenario 85M is selected is higher than 99%. It is also found that when the weight of the road condition is higher than 50%, scenario 85M is unlikely to be selected.

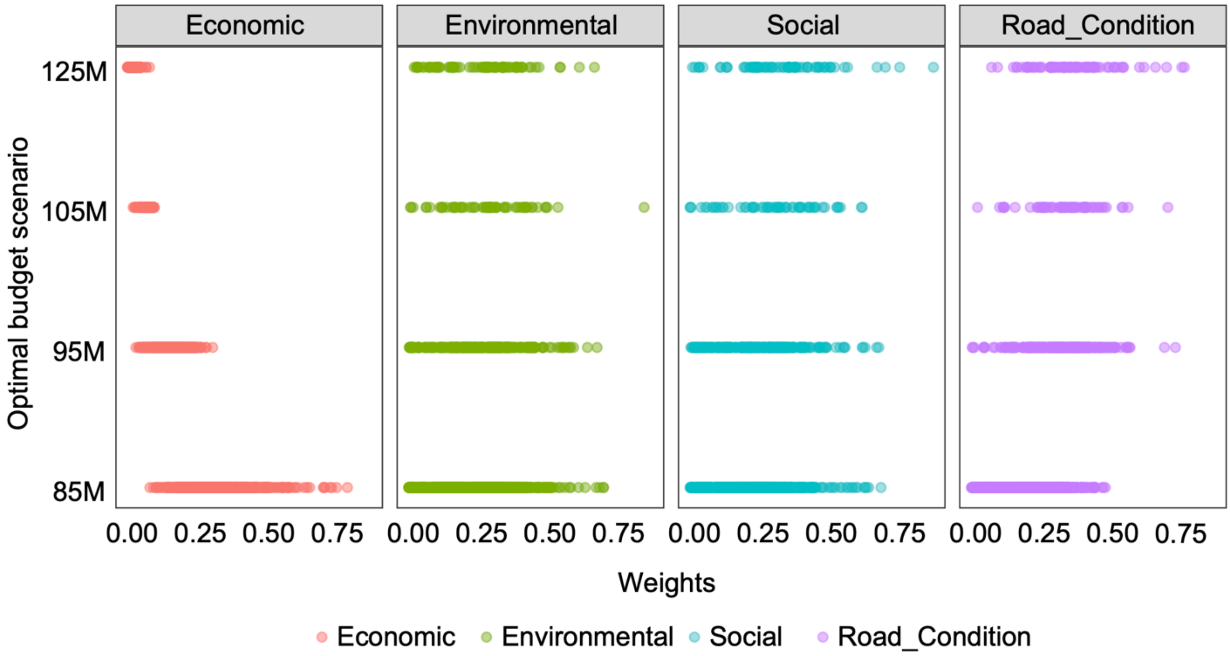

Figure 7. Relationships between optimal scenarios and the weights of the four attributes

5. Discussion

Selecting an optimal network-level pavement maintenance plan is critical for road agencies because of limited maintenance funds. Road condition and direct cost are the most frequently considered factors when evaluating a pavement maintenance plan. However, social sustainability factors such as road user costs, which are impacted by maintenance activities and improved road conditions, are rarely considered. In addition, as GHG emissions reduction has become a target worldwide under the Paris Agreement, environmental sustainability also needs to be considered in such an evaluation. Arif et al. (2016) developed a decision-making framework to support infrastructure maintenance investment decision-making that considers physical condition and socioeconomic performance. However, environmental contributions are not included, and the required data are difficult for road agencies to obtain. Batouli et al. (2017) considered road user cost, but a general unit value was adopted from the literature to calculate VOC, which limits its implications for road agencies of various countries. A practical framework is therefore proposed in this work for road agencies to accurately evaluate network-level pavement maintenance plans based on road conditions, economic, environmental, and social performance.

Under this framework, road conditions and economic performance of the network-level pavement maintenance plans are evaluated by road roughness, represented by the IRI and agency cost, respectively. Compared to the road condition assessment method adopted by Arif et al. (2016), IRI is more universally accepted and can be adapted to various countries (Du et al., 2014). To assess the environmental impact, the GWP of GHG emissions was evaluated for the network-level maintenance plans. In addition, road user cost is considered to assess social sustainability, including travel delay cost, VOC generated through fuel use, vehicle repair and maintenance, and tire wear. By integrating environmental and social considerations, this framework provides a more realistic representation of sustainability when meeting the budget and road use requirements. This provides optimal results for road agencies as they are taking increasing responsibility toward sustainability (PIARC, 2019).

It is worth mentioning that the selection of the aforementioned criteria are based on a previous study by France-Mensah and O'Brien (2019). Modifications have been made to improve the completeness and accuracy. France-Mensah and O'Brien (2019) aimed to maximize road conditions and minimize GHG emissions and road user cost. However, economic aspect was not included. As the maintenance of pavement networks is long-term work, life cycle agency cost has been and will be one of the important considerations for road agencies. In addition, in their model, average emissions and road user cost data are used, which can cause accuracy issues for network-level calculations. For example, traffic delay (such as queueing), as one indicator in road user cost calculation, is affected by road capacity and on-road traffic volume. Therefore, queueing does not occur on every road segment and usually only occurs during peak hours. Using average data for all road segments can lead to much higher emissions and traffic delay costs when compared to real-life cases. In addition, the rolling resistance effect can be affected by both the road condition and speed limit, which vary significantly among different road segments. The average data cannot be used to accurately calculate emissions from rolling resistance. To address these limitations, a hybrid LCA model that is specifically developed for estimating GHG emissions of the maintenance and use phases of roads is adopted. This model was proven to have higher accuracy than individual process-based or Tiered hybrid LCA methods in a prior study by Jiang et al. (2020).

As multiple attributes have different unit measures, it is not easy to combine them into a single score. As such, a multi-attribute method is used to compute a combined index that reflects all four attributes simultaneously. The following three steps are followed. First, weights are allocated to attributes according to their importance. Equal weights are the easiest to implement while still generating sufficiently good results (Zhang, 2014). Road agencies can reassess the weights based on their own organizational requirements. Second, the quantified performance of the network-level pavement maintenance plans is rescaled to fit in a range from 0 to 1 to enable comparability. Finally, a combined index is computed for each plan using a WSM. This approach provides an easy way for road agencies to select an optimal network-level pavement maintenance plan.

The effectiveness of the proposed framework is demonstrated in a case study of eight budget scenarios ranging from 50M to 125M. The results show that when equal weights are allocated to the four attributes, the 85M maintenance budget scenario has the lowest agency cost, with an equivalent value of AUD$6,745.06/km per year within 10 years. The most costly is the 50M scenario with, an NAV of AUD$7,388.22/km. The 50M scenario also generates the highest GWP, which is 520.33 tCO_2-e/km. On the contrary, the lowest GWP of 519.68 tCO_2-e/km is generated by the 105M scenario. In addition, 1000 random sets of weights are generated for the four attributes to determine whether there are other potentially optimal scenarios under the proposed evaluation framework when different weights are used. Scenarios 85M, 95M, 125M, and 105M are identified as potentially optimal options with probabilities of 59.6%, 26.6%, 7.7%, and 6.1%, respectively. Such a method can be used to predict the best maintenance budget scenario when road agencies are unable to give an exact weight of each attribute, but would like to evaluate maintenance options to obtain preliminary insights. Detailed results are also provided in Table S3 with an instruction in which road agencies could select a set of weights to approximate their preference and obtain the corresponding optimal scenario.

Due to the different characteristics of the selected cases (e.g., the maintenance strategies, maintenance budgets, the length of the network, road width, etc.), it is very difficult to compare the network-level results to existing studies/projects even with a similar approach. To ensure the accuracy of results, data and the calculated results of separate road segments were carefully checked and/or compared with existing literature/projects wherever possible before they were aggregated. First, for road conditions, the IRI of each road segment was provided by Main Roads, which is accurate. The calculation of the average IRI of the network is relatively direct and is unlikely to introduce uncertainty to the results. Similarly, the results for the calculated network-level agency cost should be reliable. Second, for the calculation of GHG emissions, both the method and results have been validated in a previous study by Jiang et al. (2020). The method has been proven to provide more accurate results for road agencies than process-based or individual tiered hybrid method. Detailed results for each emission source were also presented and validated in this paper. In addition, for road user cost, research is limited. Salmon et al. (2020) did not report their results for separate attributes. France-Mensah and O'Brien (2019) only reported travel delay cost per AADT per lane mile. Vehicle operating cost was not reported and the lane width was not mentioned. Paik (2018) reported the road user cost for each of the maintenance strategy applied on 1 m^2 of road pavement. However, this study calculated the annual road user costs for road segments and aggregated them. Therefore, it is difficult to conduct the comparison. To lower the uncertainty to the maximum extent, the magnitude of the results for road user cost has been checked by comparing to the parameters given in Transport and Infrastructure Council (2016). The uncertainty of the results exists but should not affect the implementation of the proposed framework.

Uncertainty also exists in the prediction of IRI and the assumptions on discount rate and traffic growth rate. A sensitivity analysis is conducted to test the sensitivity of results to the prediction and assumptions. IRI, discount rate and traffic growth rate are varied by ±10% and ±20% to investigate the impact. Generally, decreased discount rate increases the frequency that scenario 95M is selected and decreases the selection of scenario 85M; increased IRI leads to increased selection of scenario 95M and decreased IRI tend to increase the frequency that scenarios 105M and 125M are selected. Figure 8 also shows that the selection of optimal budget scenario is most sensitive to the variation of discount rate. When the discount rate decreases by 20%, the frequency that scenario 95M is selected out of 1000 random runs increases by 192%. Due to the high sensitivity to the assumptions, the results of this case study are recommended to be cautiously used. Results for traffic growth rate are not shown in the figure because of its negligible impact. The effect of traffic growth is minimized because road user cost per km per vehicle is used to represent social performance in the proposed framework.

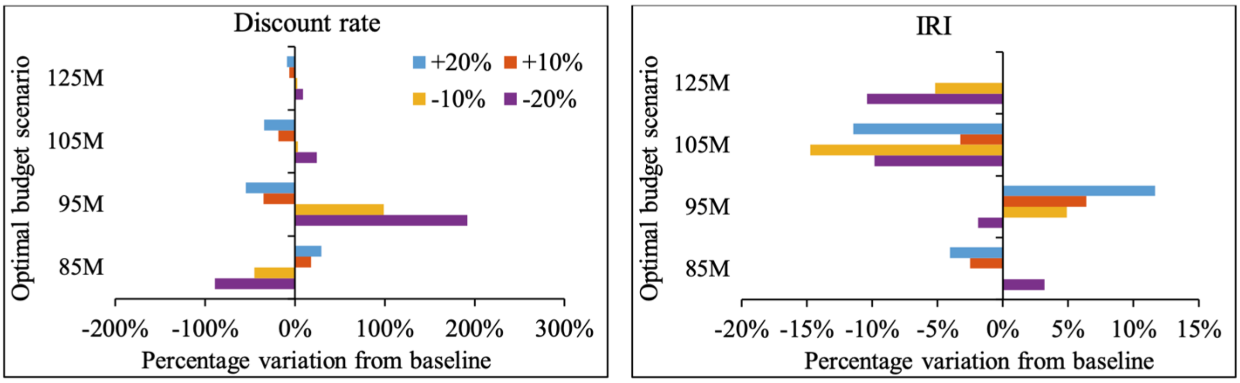

Figure 8. Sensitivity analysis for discount rate and IRI

To investigate the impact of integrating environmental and social sustainability in the framework, a similar random weighting process is implemented for a second time to exclude environmental and social sustainability. The chance that the 85M scenario is selected increases to 68.6%, a 9% increase from the case in which environmental and social factors are included. The chances that the other three scenarios are selected decrease to 20.8%, 5.0%, and 5.7%, respectively. In addition, Figure 9 presents the relationships between the selection of optimal scenarios and attribute weights when environmental and social factors are not considered. The results are highly sensitive to the weights of economic considerations and road conditions. An obvious trade-off was observed. As the weight of economic consideration increases (or the weight of road condition decreases), the optimal scenario shifts from 125M to 105M and then to 95M and 85M. On the contrary, when road conditions receive higher weight, the optimal scenario shifts from 85M to 125M.

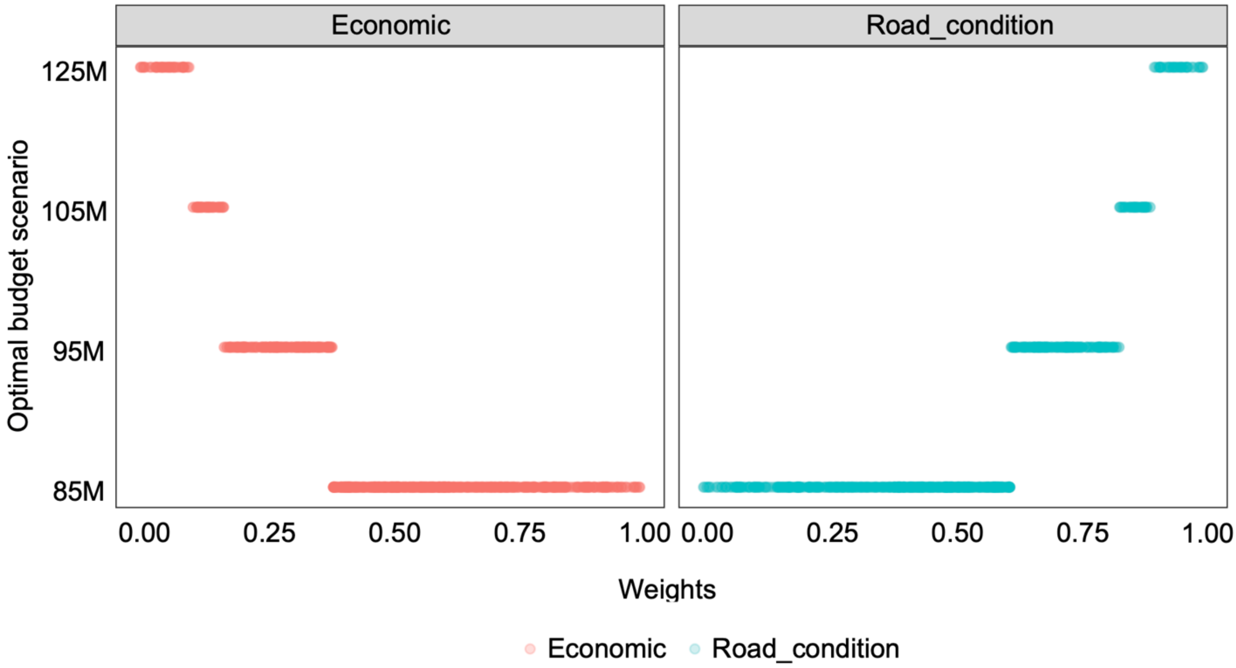

Figure 9. Relationships between optimal scenarios and the weights of the attributes (traditional method)

Although the framework is demonstrated with a road network in Australia, this framework can also be adopted by road agencies from other countries. First, making decisions for the optimal network-level pavement maintenance plan is a global concern for road agencies, as maintenance funds are limited and sustainability goals are becoming increasingly important worldwide. In addition, the data required in the proposed framework are generally easy to obtain. For example, the index for road conditions (i.e., IRI) is a universally adopted index. Agency cost and data for calculating road user costs are commonly recorded by road agencies. Data required for environmental assessments, such as the direct requirement coefficients matrix, are regularly published by national governments. To obtain GHG emission factors, many countries have developed their own emission databases.

6. Conclusions

As the number of newly constructed roads in developed countries has been limited in recent years, it is imperative that pavement maintenance plans are established to ensure that maximum sustainable benefits, including economic, environmental, and social benefits, can be achieved. Therefore, this study investigates how sustainability indicators can be integrated into the traditional assessment of a network-level pavement maintenance plan for informed decision-making. A framework is developed to help select the optimal network-level pavement maintenance plan based on pavement conditions and economic, environmental, and social sustainability. IRI, agency cost, GHG emissions, and road user cost were evaluated. The specific conditions and characteristics of each road segment are considered in the modeling of the four attributes to enable accurate calculation. To combine the four attributes and enable comparability among different network-level pavement maintenance plans, a multi-attribute decision-making method is adopted to convert the results to a single index. This framework provides a straightforward method for evaluating and selecting the optimal network-level pavement maintenance plan.

The proposed framework is demonstrated with eight network-level pavement maintenance scenarios under various annual budgets of AUD$50M, 60M, 70M, 85M, 95M, 105M, 115M, and 125M. The results show that road conditions and social performance improve as the maintenance budget increases. When equal weight is given to the four attributes, the 85M scenario is selected as the optimal maintenance scenario for the studied network. By assigning different weights to the four attributes, the 85M, 95M, 125M, and 105M scenarios are identified as potentially optimal solutions. The results also show that integrating environmental and social sustainability in the framework is necessary, as they can affect the optimal scenario significantly when they have higher weights.

It should be noted that this study has certain limitations. For example, considering the applicability and data accessibility, only roughness and GHG emissions are considered for road conditions and environmental sustainability, respectively. For future studies, it is recommended to include more indicators (e.g., cracking, rutting, and deflection for road conditions and other impact categories for environmental sustainability). Due to the unique characteristics of the selected cases (e.g., the maintenance strategies, maintenance budgets, the selected functional unit, road width, etc.), it is very difficult to compare the results of the case study to existing studies even with a similar approach. Therefore, the uncertainty in the results of the case study, although does not affect the implementation of the proposed framework, needs to be considered if they are to be used. In addition, the weights of the attributes were generated through random runs in this study. Future research may consider obtaining accurate weights using other methods such as a tradeoff or an analytic hierarchy process method to provide agency-specific recommendations.

Declaration of Completing Interest

None.

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