Sustainable pavement maintenance and rehabilitation planning using the marine predator optimisation algorithm

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Abstract

The sustainability of pavement, especially in Maintenance and Rehabilitation (M&R) scheduling, has become an immense concern and has received limited attention in previous studies. Therefore, this study aimed to develop the M&R scheduling optimisation based on sustainability. To this end, a novel sustainability index was introduced, in which all the sustainable development aspects were considered, including highway agency cost, environmental impacts, and social effects. A conventional model was used to assess the sustainable model's effectiveness. Two new constraints are introduced to reduce the budget fluctuation and not to apply the M&R treatments for two consecutive years to make the model practical. On the other hand, highway agencies face large-scale networks, in which the optimisation of M&R scheduling has computational complexities. Thus, the novel and powerful metaheuristic algorithm, named Marine Predator Algorithm (MPA), was applied to solve the pavement M&R scheduling problem. A large-scale pavement network, including 110 sections, was analysed over a 5-year plan as the case study. The results indicated that using the sustainable model rather than the conventional one leads to a 6.5% reduction in CO_2 emission. Besides, utilising the sustainable approach enhances the equity and safety indices by 40.7% and 2.5% compared to the conventional treatment. However, the highway agency cost is increased by 1.1% using the sustainable model.

Keywords: Pavement management system; Pavement maintenance and rehabilitation planning; Marine predator algorithm; Sustainability; Environment

1. Introduction

Infrastructure systems are fundamental tools to improve and reinforce economic growth. Transportation infrastructures are significant parts of infrastructure systems that are largely dependent on pavement, which can deteriorate over time. Maintenance and Rehabilitation (M&R) treatments provide services to preserve pavement and keep them in a serviceable condition (Mandiartha et al., 2017). In the early 1960s, the Pavement Management System (PMS) emerged to provide essential means for transportation decision-makers and agencies to achieve optimal strategies for maintaining pavement in an acceptable condition over time (Haas et al., 2015).

An efficient PMS maintains the pavement networks at the desired service level and structural condition (Meneses & Ferreira, 2012). The main challenge encountering Road Maintenance and Transportation Organisation (RMTO) managers is to preserve road networks at an acceptable level of serviceability under the rigorous annual M&R budgets (De La Garza et al., 2011). Therefore, the selection and optimisation of M&R efficient plans at the network level are critical objectives of a PMS.

Modelling scheduling optimisation of M&R in pavement networks presents a mixed-integer optimisation problem. Many researchers have used exact optimisation algorithms to solve this M&R optimisation problem. For instance, Li et al. (1998) applied cost-effectiveness-based integer M&R scheduling to assess the minimum budget needed for maintaining a pavement network performance at an acceptable level. A pavement network consisting of five sections was utilised as their case study. Seyedshohadaie et al. (2010) employed two linear programming models to optimise M&R scheduling for a pavement network consisting of 20 sections.

Al-Amin (2013) used linear integer programming to solve the pavement M&R

planning problem under budget restriction, which included ten pavement sections in the case study. The author expressed that the model was only applicable to small-scale network problems due to computational complexities.

The complexity of the pavement M&R problems amplify exponentially as the number of the pavement network's sections increases. In this regard, considering several pavement sections in the M&R planning problem makes the problem a non-deterministic polynomial-time problem (NP-hard). However, exact optimisation algorithms are not able to solve NP-hard problems due to restrictions for solving complex problems, such as scheduling M&R for large-scale networks. Hence, the application of metaheuristic algorithms can be an appropriate option to approach the above-mentioned high-level complexity (Naseri et al., 2021).

The Genetic Algorithm (GA) has been used by numerous researchers to schedule M&R for large-scale pavement networks, which was initially performed by Chan et al. in 1994 to solve pavement M&R scheduling problems. Moreover, Ferreira et al. (2002) employed GA to optimise the M&R planning problem. To this end, the authors aimed to minimise the total costs involved in the planning M&R treatments that were implemented in the sections of a given network over a planning period. Mathew and Isaac (2014) proposed GA to resolve the multi-year M&R planning problem for rural roads at the network level. The results indicated that GA was highly effective in finding the optimal solution for the M&R scheduling problem.

Hafez et al. (2018) utilised GA to schedule M&R treatments on low-volume sections. The results of the study were implemented on a large-scale network consisting of 85 sections. By employing GA to solve an M&R problem, Khavandi Khiavi and Mohammadi (2018) minimised both user and highway agency costs and maximised the residual value of pavements at the end of the evaluation period. Elhadidy et al. (2020) aimed to minimise costs and maximise conditions using GA to solve the M&R scheduling problem at the network level, which contained 51 sections.

In the last decade, newer metaheuristic and convolutional algorithms have more frequently appeared in studies on M&R scheduling than the traditional GA. Some researchers have also compared the performance of diverse metaheuristic algorithms. For instance, Tayebi et al. (2014) applied Particle Swarm Optimisation algorithm (PSO) and GA to pavement M&R scheduling at the network level, concluding that PSO was able to solve the problem faster and provide a better solution.

Naseri et al. (2020) demonstrated a mixed-integer programming pavement M&R scheduling model by employing GA and the Water Cycle Algorithm (WCA) to solve the problem. In the case study, the authors investigated 103 pavement sections and deduced that WCA was faster than GA and, thus, has superior performance. Although it was introduced by Eskandar et al. in 2012, the researchers claim that WCA is a novel algorithm. Importantly, they postulated that metaheuristic algorithms are highly qualified to solve large-scale M&R scheduling problems. In addition, Naseri et al. (2021) represented that newer metaheuristic and evolutionary algorithms defeated the GA in optimising the planning of M&R treatments planning, and GA's performed much weaker than newer algorithms.

While previous studies have mainly focused only on economic and technical terms, the significance of other sustainability aspects of the M&R scheduling has been disregarded (Hankach et al., 2019). As suggested by Strezov et al. (2017), sustainable development consists of three dimensions: economic, environmental, and social. Therefore, it is pertinent to consider all three elements in sustainable M&R scheduling;

yet, recent researches have failed to do so. Although cost-effective M&R scheduling enhances the economic aspect of the system, it disregards environmental impacts and social growth.

Regarding the environment, the transportation industry is the second-largest source of GHG emissions globally (Ang & Marchal, 2013), which is largely attributed to carbon dioxide (CO_2) release (Cross et al., 2011). Greenhouse gas (GHG) emissions has to be taken into account to assess environmental impacts (Naseri et al., 2020). Remarkable quantities of energy are consumed and significant amounts of the GHG emissions are released in the production of the pavement components, pavement construction, and M&R during the entire pavement life cycle (Santos et al., 2018). In global terms, the transportation industry accounted for 24% of the world's CO_2 emissions from fossil fuel combustion in 2020. Particularly, road transport, which plays a vital role in the transportation industry, is responsible for three-quarters of transport pollution (IEA, 2020).

Some studies have investigated and aimed to minimise GHG emissions due to their detrimental effects. Torres-Machi et al. (2017) designed M&R programs considering the effects of GHG emissions with the intent to maximise the long-term efficiency of the pavement network and to minimise GHG emissions by the implementation of the M&R treatments. Santos et al. (2017) utilised GA to minimise the road authority and the user life cycle costs. Lee and Madanat (2017) posed an optimisation model to reduce GHG emissions under various budget constraints and suggested a computationally efficient bottom-up approach using Lagrangian relaxation and dynamic programming. Choi (2019) defined three scenarios, each investigated with various M&R treatments. The purpose of the study was to achieve a scenario with the lowest cost and lowest CO_2

emission.

Al-Saadi et al. (2020) utilised the simulated constraint boundary model to present a pavement preservation strategy at the network level. The model concentrated on two targets: minimising highway agency costs and reducing CO_2 emission. The model constraints included the total budget threshold for pavement M&R and the unallowable limit of pavement roughness. All studies mentioned above agree and prove that CO_2 emissions should be considered in pavement M&R planning in order to protect the environment.

The pavement network's social dimension is a substantial aspect of sustainability since it addresses the consequences of the network on users and residents. As another vital aspect of sustainability, the social effects have not received enough attention in the PMS by previous research. Previous studies have focused on equity, which is characterised as the fair allocation of the M&R budget according to pavement segments in need of intervention (France-Mensah & O'Brien, 2018). The sense of welfare and well-being is significantly improved by considering equity.

In the case of equal allocation of resources over a large region, Boyles (2015) considered equity concerns in the infrastructure M&R scheduling. However, the chosen equity metric was not appropriate and, thus, unable to reflect equity properly. Recently, Naseri et al. (2020a) developed a novel index named the equity index using sensitivity analysis, expert justice, and engineering analysis. The index demonstrated justice well and was used to investigate the equity between various individuals using different segments of the network. However, the equity index was not taken into consideration in pavement M&R planning and was only employed to compare the outcomes of two metaheuristic algorithms. Several researchers used other social criteria to plan M&R

treatments. In this regard, Gao and Zhang (2013) considered vehicle operating costs and travel delay costs to optimise M&R activities. The authors employed the mentioned costs as the social criteria to plan M&R treatments. Moreover, user costs were taken into consideration as the social aspect by Santos et al. (2018). Besides, Justo-Silva and Ferreira (2019) employed the road accident cost component as a social aspect. The authors stated that road accident cost represents the economic value of damages caused by vehicle accident, which is important. Considering the above-mentioned issues facing pavement M&R, the presented study aimed to implement a modernised approach to find proper solutions. That is, this study attempts to propose a new approach to optimise all three sustainability pillars (i.e., minimising agency cost, minimising different environmental factors, maximising social benefits) as well as enhance the condition of pavements.

2. Objective and scope

The current research aimed to develop an optimisation model that can solve the problem of large-scale pavement M&R scheduling by considering sustainability. Contrary to previous investigations, economic, environmental, and social aspects were taken into account simultaneously, employing the equity index and safety index as representative of the social effects. In addition, GHG emissions was considered as environmental indices to plan the M&R.

Finally, highway agency cost, GHG emissions, equity index, and safety index served as the objective functions, which were not investigated together in previous researches. Moreover, the available budget and pavement condition were applied as constraints in the optimisation model. In addition, the fluctuation of the annual budget was confined to a predetermined amount. Additionally, a novel metaheuristic algorithm, named Marine Predator Algorithm (MPA), recently developed by Faramarzi et al. (2020), was developed to simultaneously optimise solutions and sustainability. Furthermore, a new constraint was introduced to prevent the optimisation model from allocating maintenance activities for a section in two consecutive years and increase the practicality of the model.

3. Methodology

The current study aimed to establish the optimal M&R treatments by considering sustainability for a large-scale flexible pavement network. Furthermore, all three sustainability aspects were investigated to minimise cost, improve the environmental impacts, and enhance social benefits. In this regard, a novel optimisation modelling was introduced in this study to enhance all the mentioned sustainability criteria simultaneously. In addition, a new constraint was developed and applied in the proposed model to increase its applicability.

To develop the methodology, an indicator was first selected to demonstrate the pavement condition. Then, a pavement deterioration function was chosen based on the selected pavement performance indicator. In the next step, two pavement optimisation models, i.e. sustainable and conventional models, were developed and used to plan M&R treatments. The sustainable model considers the sustainability criteria as the problem's objective function, while the conventional model overlooks sustainability in the problem modelling. To this end, a new approach was utilised to acquire a sustainability index and environmental index. Afterward, the new metaheuristic algorithm, denoted Marine Predator Algorithm (MPA), was adapted to solve the M&R scheduling optimisation problem. Ultimately, the solutions obtained from both the sustainable and conventional approaches were compared. Figure 1 presents the flowchart of the steps adopted for the current study, which are described in detail in the following sections.

Insert Figure 1 Here

3.1. Pavement deterioration modelling

The PMS uses several indicators to assess pavement performance and pavement roughness, one of the most representative indicators (Wang et al., 2007), measured by the International Roughness Index (IRI). It has been proven that IRI strongly correlates pavement structural distresses, serviceability, safety, and driver convenience (Osorio-Lird et al., 2018; Abdelaziz et al., 2020). Furthermore, reduced IRI leads to decreased user cost, improved driver comfort, and minimised travel time. The six elements that affect IRI include environmental impacts, cracking, potholing, rutting, patching, and structural deformation (Bannour et al., 2019). Since RMTO gathers data based on IRI in order to optimise M&R scheduling, IRI was selected as the pavement indicator. It is pertinent to note that the optimisation model presented in the following sections is also compatible with other indicators, such as the Pavement Condition Index (PCI).

Pavement deteriorates over time due to its high usage, which leads to increased IRI. Various IRI prediction models have been generated since the precision of these models plays a vital role in M&R planning. For instance, Tsunokawa and Schofer (1994) introduced an applicable and well-known IRI performance function, using World Bank data to evaluate the format of the performance function. The mentioned performance function was used to model the deterioration process as an exponential function of time, which is represented in Equation (1):

$$IRI_{it} = IRI_{it^0} \exp(\beta(t - t^0)) \tag{1}$$

where IRI_{it} is the roughness of the pavement section i at time period t; IRI_{it^0} is the initial roughness of the section i at time period t; and β is the deterioration rate. The above-mentioned IRI performance function is extensively used at both project and network levels in the previous studies (Li and Madanat, 2002; Seyedshohadaie et al., 2010; Gao and Zhang, 2012).

3.2. Sustainable pavement M&R optimisation modelling

In the current study, sustainable and conventional models were adopted, in which the former considers sustainability as the objective function, while the latter neglects sustainability. By applying both models, this study aimed to assess the effectiveness of sustainability on the optimisation of M&R scheduling. The mixed-integer programming model for network-level pavement M&R planning for the first approach (sustainability) is formulated according to Equation (2) to (12):

$$\text{Minimize } z_1 = SI \tag{2}$$

s.t:

$$\sum_{i=1}^{I}\sum_{k=1}^{K} A_i \times C_{k,t} \times x_{i,k,t} \le B_t \qquad \forall t \in \{1,2,...,T\} \tag{3}$$

$$IRI_{i,t+1} = (IRI_{i,t} \times \exp(\beta)) - (\sum_{k=1}^{K} \text{Improvement}_{i,k,t+1} \times x_{i,k,t}) \qquad \forall i \in \{1,2,...,I\} \tag{4}$$

$$IRI_{net,t} = \frac{\sum_{i=1}^{I} IRI_{i,t} \times A_i}{\sum_{i=1}^{I} A_i} \qquad \forall t \in \{1,2,...,T\} \tag{5}$$

$$IRI_{net,T} \le E \times IRI_{net,0} \tag{6}$$

$$IRI_{i,t} \ge IRI_{\min} \qquad \forall t \in \{1,2,...,T\} \tag{7}$$

$$IRI_{i,t} \le IRI_{\max} \qquad \forall t \in \{1,2,...,T\} \tag{8}$$

$$Min\left\{\sum_{i=1}^{I}\sum_{k=1}^{K} A_i \times C_{k,t} \times x_{i,k,t}\right\} \ge G \times Max\left\{\sum_{i=1}^{I}\sum_{k=1}^{K} A_i \times C_{k,t} \times x_{i,k,t}\right\} \quad \forall t \in \{1,2,...,T\} \tag{9}$$

$$x_{i,1,t} + x_{i,1,t+1} = 1 \tag{10}$$

$$\sum_{k=1}^{K} x_{i,k,t} = 1 \qquad \forall i \in \{1,2,...,I\}, \quad \forall t \in \{1,2,...,T\} \tag{11}$$

$$x_{i,k,t} \in \{0,1\} \tag{12}$$

where SI signifies the sustainability index. A_i, $C_{k,t}$ and B_t are the area of section

i, the unit cost of treatment k applied to the section i at the of t, and the budget allocated for M&R treatments at the time of t, respectively. $IRI_{i,t}$ denotes the IRI of section i at the time of t. $IRI_{net,t}$, $IRI_{net,0}$, $IRI_{\min}$ and $IRI_{\max}$ represents the weighted average IRI of the network at year t, the weighted average IRI of the network at year 0, maximum acceptable IRI, and minimum acceptable IRI, respectively. $\text{Improvement}_{i,k,t}$ refers to the IRI drop caused by the application of treatment k to the section i at the of t. E is the pavement network improvement threshold. E has to be lower than one since Eq. (6) ensures that the IRI of the network at the end of the planning period should be lower than its initial IRI. For instance, when E is equal to 0.7, the network's IRI at the end of the analysis period have to reduce at least by 30% compared to the initial network's IRI. G is the budget restriction limit. $x_{i,k,t}$ is a binary decision variable that is either 1 or 0. $x_{i,k,t}$ represents the treatment k applied to section i at the time of t. I, K and T denote the number of the sections in the investigated network, number of M&R treatments, and number of years in the analysis period, respectively.

Equation (1) is used to calculate the IRI and improvement results from the M&R treatments. The following equations each describe different constraints. Equation (2) displays the optimisation problem's objective function, which is to minimise the sustainability index, as explained in the next section. Equation (3) ensures that the total agency costs of the M&R treatments in each time period are less than the existing budget. Equation (4) computes the IRI of each section based on the deterioration process and treatment's improvement. The area and IRI of sections used to define the IRI of the network are given by Equation (5). Considering that the RMTO aims to improve the network's IRI, Equation (6) guarantees that the network's IRI at the end of the planning horizon is less than the desired level. To this end, the value of parameter E specifies how many the network's IRI should have to decrease at the end of the planning period compared to its initial IRI. Hence, by using this constraint, the highway agency ensures that the network's IRI at the end of the planning period will decrease, and its condition will enhance.

Equation (7) shows that the IRI of each section cannot be lower than the minimum allowable IRI. Also, Equation (8) indicates that the pavement IRI has to be lower than the maximum IRI value. Equation (9) reduces the budget fluctuation in the planning period, which increases the applicability of the model since the budget cannot be expanded by more than a determined value by most highway agencies. Hence, the highway agency ensures that the fluctuation between the minimum and maximum of the required budget is not considerable. Therefore, the highway agency will be able to provide enough financial resources since the fluctuations of the required budget are insignificant. In this regard, allocating the required budget for the organisation is possible, which makes the model exceptionally practical because many highway agencies are not able to plan M&R treatments optimally. Equation (10) implies that if an M&R treatment is applied on a pavement section, the M&R treatments cannot be performed on it the following year. The reason for this constraint, which enhances the practicality of the model, is that according to the RMTO's objectives, it is not possible to implement the M&R treatments for two consecutive years on one pavement section. Just one M&R treatment alternative can be selected for each section in each year, which is ensured by Equation (11). Equation (12) represents the binary decision variable $x_{i,k,t}$ of treatment k applied to section i at the time of t, which is set to 1 if the treatment has been chosen and 0 otherwise.

The second, or conventional, model does not consider sustainability. That is, it is modelled to minimize total M&R costs, and its objective function is shown in Equation

(13).

$$\text{Minimize } z_2 = \sum_{i=1}^{I} \sum_{k=1}^{K} A_i \times C_{k,t} \times x_{i,k,t} \qquad \forall t \in \{1, 2, ..., T\} \tag{13}$$

As mentioned, A_i and $C_{k,t}$ are the area of section i, the unit cost of treatment k applied to the section i at the of t. Moreover, $x_{i,k,t}$ is a binary decision variable, which is set to 1 if treatment k applied to section i at the time of t, and otherwise it is equal 0. Equation (13) minimises the total M&R costs during the analysis period. Also, the constraints of the conventional method are the same as the sustainable model (Equation (2) to (12)).

3.3. Sustainability index

As explained, sustainable development consists of three components: economic, environmental, and social. The highway agency cost, as the representative of the economic dimension, was evaluated using Equation (14). For the environmental dimension, CO_2 emissions was determined by Equation (15):

$$AC = \sum_{i=1}^{I} \sum_{t=1}^{T} \sum_{k=1}^{K} A_i \times C_{i,k,t} \times x_{i,k,t} \tag{14}$$

$$CO_{2\ Total} = \sum_{i=1}^{I} \sum_{t=1}^{T} \sum_{k=1}^{K} A_i \times CO_{i,k,t} \times x_{i,k,t} \tag{15}$$

where AC refers to the agency cost. $CO_{2\ Total}$ implies the total amount of CO_2 emissions. $CO_{i,k,t}$ is the unit CO_2 emission of treatment k applied to section i at time t. Equation (14) presents the highway agency cost for treatment k implemented to section i at time t. Equations (15) is used to calculate the total amount of CO_2 emissions in the planning horizon, respectively.

To unify agency cost and CO_2 emission, CO_2 emission is converted to its equivalent price (carbon price). Therefore, the carbon price is calculated by Equation (16). Subsequently, total cost is calculated using Equation (17):

$$CO_{2\ Total}^{price} = \sum_{i=1}^{I}\sum_{t=1}^{T}\sum_{k=1}^{K} A_i \times CO_{i,k,t} \times U_{CO_2}^{price} \times x_{i,k,t} \tag{16}$$

$$TC = AC + CO_{2\ Total}^{price} \tag{17}$$

Where $CO_{2\ Total}^{price}$ and $U_{CO_2}^{price}$ represent the total price of CO_2 emission and unit price of CO_2 emission (the equivalent price of each kg CO_2). TC is the total cost calculated by summation of agency cost and price of CO_2 emission.

Total cost should be scaled between 0 and 1 so that its effect on the objective function is equal to other parameters (Shirzadi Javid et al., 2020). To this end, the minimum and maximum values of this parameters should be calculated. For this purpose, maximisation of TC was considered as the optimisation problem's objective function (placed in Equation (2)) separately. Subsequently, the model was run 30 times, and the maximum value of this parameter was assessed through an optimisation problem by considering all constraints (Equations (3-12)). Hence, the maximum value of TC was calculated. Consequently, the minimum value of this parameter was considered zero to to make all objective function components homogenous. Then, Equation (18) was utilised to normalise the environmental impact values (Naseri et al., 2019):

$$S_H = \frac{H - H_{\min}}{H_{\max} - H_{\min}} \tag{18}$$

In terms of social impacts, the equity index and safety index are considered in the sustainability model. The equity index, recently introduced by Naseri et al. (2020a), was considered as a social indicator. Since a notable difference between the IRI of the different sections in a network leads to driver dissatisfaction, highway agencies aim to reduce the pavement IRI variance between sections. Therefore, the equity index was used to evaluate the level of equity resulting from the optimisation models, as indicated in Equation (19):

$$EI = \frac{IRI_{\max,T} - IRI_{\min,T}}{10} + \frac{\sum_{i=1}^{n} AADT_i \times \left| IRI_{i,T} - IRI_{net,T} \right|^3}{n \times \sum_{i=1}^{n} AADT_i} \tag{19}$$

where $IRI_{\max,T}$, $IRI_{\min,T}$ and $IRI_{net,T}$ imply the maximum, minimum IRI of sections, and network IRI in the last year of analysis period, respectively. n is the number of pavement sections in a network. $AADT$ stands for the annual average daily traffic. According to Equation (19), it is inferred that the highway agencies should pay more attention to high volume roads than low volume roads. The ideal value of equity index is 0, which is obtained when all sections of a network have equal IRI in the last year of analysis period. Hence, if the value of equity index rises, the equity over the network is reduced.

Safety index is the other parameter to maximize social benefits in the pavement M&R plan. Health and Safety is today one of the vital advanced fields of the social policy of the international level (Benoît Norris et al., 2013). Therefore, safety plays a crucial role in sustainability development, and it should be considered in different projects to enhance sustainability. It has been proved that IRI significantly affects safety since IRI increment leads to an increase in the number of total crashes (Jaeyoung Lee & Abdel-Aty, 2019). Sharif Tehrani et al. (2017) investigated the parameters affecting road safety using a Zero Inflated Poisson Regression, and the results indicated that IRI and AADT were the most effective parameters on the number of total crashes. Moreover, they presented a model to estimate the number of crashes in a three-year analysis period. The presented model was adjusted to calculate the number of annual total crashes, and it is represented in Equation (20).

$$SA = \sum_{i=1}^{n}\sum_{t=1}^{T} 0.025 \times AADT_i + 1.667 \times 10^{-5} \times IRI_{it} \qquad (20)$$

where SA is the safety index. IRI_{it} and $AADT_i$ imply the IRI of section i at time t and the annual average daily traffic of section i. Based on Equation (20), reducing IRI and AADT results in increasing safety in the network. Considering this index as one of the objective functions in the pavement M&R optimization can reduce the number of crashes during the planning horizon, and hence, health and safety are increased.

As done for the total cost, the maximum values of the equity index and safety index were calculated. In this regard, maximisation of each of these parameters was set to the objective function and problem, and each model was run 30 times considering the constraints (Equations (3-12)). Therefore, the maximum value of equity index and safety index were calculated. Similar to total cost, the minimum value of social impacts (i.e., equity index and safety index) was considered zero. Subsequently, these minimum and maximum values were employed to normalise the equity index and safety index. Consequently, the social index was modelled using the scaled values of equity index and safety index, shown in Equation (21):

$$SOC = \mu_1 S_{EI} + \mu_2 S_{SA} \qquad \sum_{l=1}^{L} \mu_l = 1 \qquad (21)$$

where S_{EI} and S_{SA} imply the scaled amount of equity index and safety index, respectively. μ_1 and μ_2 signify the coefficient of equity index and safety index in the social index, respectively. SOC represents the social index in which the summation of μ_1 and μ_2 is equal to 1; thus, SOC is scaled between 0 and 1.

Then, total cost (combination of agency cost and CO2 emissions) and social index are considered in the sustainability index in Equation (22):

$$SI = S_{TC} + SOC \tag{22}$$

where SI is the sustainability index. S_{TC} and SOC indicate the scaled total cost and social index, respectively. These parameters were scaled to have the same importance in the objective function; therefore, the weight of each parameter was the same.

3.4. Marine Predator Algorithm (MPA)

As previously mentioned, exact optimisation algorithms falter due to the high-level complexity of NP-hard optimisation problems, such as those facing large-scale pavement M&R planning. To this end, metaheuristic and evolutionary optimisation algorithms have been extensively employed to manage such high-level complexity (Naseri et al., 2022). A more detailed look at the literature reveals that most of the researchers utilised GA to solve the pavement M&R planning optimisation problems. However, the application of recently-developed and robust metaheuristic algorithms to solve the mentioned problems has not received enough attention. In this regard, a recently-proposed and powerful metaheuristic algorithm, called Marine Predator Algorithm (MPA), was adjusted to solve the complex optimisation problems modelled in this investigation.

Faramarzi et al. (2020) introduced MPA and compared its performance with those of the most applicable metaheuristic and evolutionary optimisation algorithms using 58 mathematical benchmark functions. The results indicated that MPA considerably outperforms GA, Particle Swarm Optimisation, Gravitational Search Algorithm, Cuckoo Search, Salp Swarm Algorithm and Covariance Matrix Adaptation Evolution Strategy. Therefore, MPA can be an appropriate algorithm to be applied in large-scale pavement M&R scheduling problems.

In theory, MPA was inspired by the hunting pattern of ocean predators to find the optimal solution to the optimisation problems. The algorithm considers both prey and predators as search agents (solution vectors), whereby their movement and tasks change during iterations (Faramarzi et al., 2020). The movement strategies include Lévy movement and Brownian movement to obtain their ideal goals, which vary according to the predators' purpose to hunt and the prey's aim to survive (Naseri et al., 2021).

The Brownian movement is a stochastic movement, in which their movement length is generated from a Normal (Gaussian) distribution probability function with unit variance (σ2 = 1) and mean of zero (μ= 0) and. The probability density function for generating the movement length of search agent *x* is presented in Equation (23). The Lévy movement is a form of random movement, in which the movement length of search agents is calculated from a probability function defined by the power-law tail (Lévy distribution), which is indicated in Equation (24).

$$f_{Brownian}(x_i, \mu, \sigma) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\ (-\frac{(x_i - \mu)^2}{2\sigma^2}) \tag{23}$$

$$f_{Levy}(x_i) = |x_i|^{1-\alpha} \tag{24}$$

α

Where, x_i is the movement length of search agent i, and α is a random number between 1 and 2.

There are three movement strategies for prey and predators. In the first strategy, it is presumed that the prey moves faster than the predator ($S = 10$; S signifies the prey to predator speed ratio). Accordingly, exploration matters in these initial iterations, where the predator's best approach is to stop moving, and Lévy or Brownian can be the best movement strategy for the prey.

In the intermediate iterations (second movement strategy), it is assumed that the prey and predator move at the same speed ($S = 1$) and, thus, the same velocity. If the prey moves according to Lévy movement, the predator's best movement strategy is Brownian. In these iterations, both exploration and exploitation are essential for which both the prey and predator are responsible. In the final iterations (third movement strategy), only exploitation matters, and the predator moves faster than the prey ($S = 0.1$). In this phase, the most valuable moving strategy is Lévy for the predator, and prey can escape by Lévy or Brownian movement. Based on these three movement strategies, search agents investigate the feasible region, whereby the search agent with the highest fitness value is introduced as the optimisation problem's optimal solution (Faramarzi et al., 2020).

4. Case study

A large-scale network of the primary roads, including 110 flexible pavement sections, was investigated. Due to the different lengths and areas of the sections, the computational complexities were high. The RMTO collected and processed the pavement distress data using an automated data collection van with a Laser Crack Measurement System (LCMS), which was used in the case study. The purpose of the case study was to investigate all aspects of sustainability in the pavement M&R scheduling.

According to the RMTO data, the maximum and minimum IRI of the studied sections were 1.95 and 6.93 m/km in the beginning of the analysis period, and $IRI_{net,0}$ was 3.54 m/km. The RMTO aimed to reduce the IRI of the network by at least 30% ($E = 0.7$) in the last year of the analysis period (Office of Road Maintenance, 2019). Hence, the network average weighted IRI must be less than 2.48 m/km in the final planning year. According to the data collected from the RMTO, the IRI of the new constructed pavements was about 1.5 m/km. Meanwhile, the annual budget for the mentioned pavement network was determined to be 26.2 billion Tomans (Office of Road Maintenance, 2019), and $IRI_{\min}$ was considered to be 1.5 m/km. On the other hand, due to the existence of roads with a large IRI and budget and executive constraints, it is not possible to reduce the IRI below 6 m/km within a short time period, such as two years. Therefore, $IRI_{\max}$ was considered to be 6 m/km.

Previous studies have suggested that the deterioration rate (β) in trend curve models is 0.05 (Fani et al., 2020; Y. Li & Madanat, 2002; Ouyang & Madanat, 2004; Seyedshohadaie et al., 2010). The RMTO prefers that the annual budget fluctuations be less than 25% (Office of Road Maintenance, 2019); thus, G is presumed to be 0.75. μ_1 and μ_2 were considered 0.5 and 0.5. The planning horizon for the mentioned pavement network was considered for a 5-year period.

According to the road administration's M&R contracts, there are six different types of treatments applied to primary roads in Iran, including 'do nothing,' preventive maintenance type 1, preventive maintenance type 2, light rehabilitation, medium rehabilitation, and heavy rehabilitation, as shown in Table 1. Do nothing indicates that no treatment is applied, and hence, there is no improvement in the pavement condition. For preventive maintenance, this study aimed to determine which type of treatment, either crack sealing or slurry seal, is more compatible with sustainability. In the case of heavy rehabilitation, the pavement condition is considered to be new, irrespective of its prior condition. The unit cost of each treatment is represented in Tomans (Iran currency). CO_2 emission is the total CO_2 emitted to implement treatments in different phases, including material extraction, material production, mix preparation, and implementation process. The values for IRI improvement and units CO_2 emission were extracted from Giustozzi et al. (2012), Naseri et al. (2020a) and Naseri et al. (2021). The unit price of CO_2 emission

($U_{CO_2}^{price}$) was considered 0.057 Euro (Environmental Prices Handbook EU28 Version - CE Delft - EN, 2017), which is equal to 1653.171 Tomans (each Euro equals 29003 Tomans on 13 March 2022). Because the selection of the heavier types of treatments leads to more improvement, cost and CO_2 emissions are reported in a unit square meter. Hence, these values must be multiplied by the area of each section on which the treatment is applying.

Insert Table 1 Here

5. Results and discussion

The metaheuristic algorithm, named MPA, was adjusted to solve the large-scale pavement network M&R scheduling optimisation problem, using MATLAB software to model the problem. Since previous studies failed to consider all sustainability aspects, this study developed a sustainability index to consider the environmental, economic, and social aspects of sustainability to overcome deficiencies. For comparative reasons, a conventional model was employed. Both sustainable and conventional models were considered to solve the problem in order to evaluate their effectiveness. Then, solutions obtained from both procedures were compared. This investigation's results are presented in six parts, which are described as follows. First, the tuning process applied to calibrate MPA hyper-parameters is described. Afterward, the network's IRIs obtained from the two approaches are compared. Then, the costs of the two approaches' optimal solutions are discussed. Consequently, the environmental aspects of the models are presented. Subsequently, the social aspects' results of the two models are compared. Ultimately, the treatments introduced by the sustainable and conventional models are scrutinised.

5.1. Tuning MPA hyper-parameters and the results of models

The performance of metaheuristic algorithms depends on the values of their hyper-parameters. The values of the hyper-parameters should be defined by users, and considering inappropriate values leads to finding sub-optimal solutions. MPA contains four hyper-parameters, including Fish Aggregating Device (FAD), the Number of Search Agents (NSA), the Maximum Number of Iterations (MNI), and constant number (P). The hyper-parameters design vector is considered $FAD = \{0.1, 0.2, 0.5, 0.7, 0.9\}$, $NSA = \{400, 600, 800, 1000, 1200\}$, $MNI = \{1500, 2000, 2500, 3000, 3500\}$, and $P = \{0.1, 0.5, 1, 1.5, 2\}$, having a totally $5 \times 5 \times 5 \times 5 = 625$ combination of design (Faramarzi et al., 2020). Therefore, for both optimisation models (i.e., sustainable and conventional), each combination of design is run 30 times, and the combination with the least average objective function value is considered the optimal values of hyper-parameters. For the conventional model, the optimal values of FAD, P, NSA, and MNI are 0.7, 1.5, 600, and 3000, respectively. Moreover, the optimal values of FAD, P, NSA, and MNI are 0.5, 1.5, 600, and 3000, respectively, for the sustainable model, indicating that the sustainable model requires a higher FAD to find the optimal solution, and it may be related to its higher computational complexity.

The minimum, maximum, average, standard deviation, and Kurtosis of optimal objective function values obtained in different runs for both models are presented in Table 2. The range of objective function values in sustainable and conventional models is different, and it is due to the difference in the format of their objective function. Moreover, the Kurtosis indicates that both models' results follow a normal univariate distribution.

Insert Table 2 Here

5.2. IRI of the network

A primary target of the highway agencies is to reduce the average IRI of the network, thus both models aimed to reduce the IRI. The annual average of the IRI of the network is indicated in Figure 2. Both models continuously decreased the network's IRI and reached almost the same value in the final year of the analysis period. As indicated in Figure 2, both models achieved $IRI_{net,T}$ of approximately 2.48 m/km, indicating a desirable decrease from $IRI_{net,0}$ of 3.54 m/km. Therefore, both models reduced the IRI of the network by 30% by using the 5-year-planning, which is one of the most significant objectives of the RMTO. Hence, it can be suggested both models exhibited acceptable performance for achieving the reduction of IRI in the network during the planning horizon.

Insert Figure 2 Here

5.3. Cost

Cost is a substantial criterion for decision-makers to enhance sustainability, and accordingly it should be minimized in every project (Naseri, 2019). Due to the lack of budget, highway agencies look for more economical alternatives. That is to say, as the gap between maintenance cost and the available budget increases, highway agencies seek cost-effective solutions (Wu et al., 2017). If the highway agencies cannot supply the cost of the M&R treatments due to the lack of budget, the gap between planned M&R costs and the available financial resources further increases. Therefore, the cost of M&R planning is a significant criterion for the RMTO.

The outcomes of the M&R optimisation problem of the case study indicate that using the sustainable model instead of the conventional one increases M&R costs by roughly 1.3%. It can be interesting that both models reduce the network's IRI equally. Figure 3 presents the annual cost of the M&R treatments obtained from both methods in the planning horizon, which reveals that M&R costs of sustainable and conventional models are 80.79 and 79.73 billion Tomans over a 5-year period, respectively. However, the CO_2 cost of the sustainable model (33.82 billion Tomans) is 6.5% less than the conventional model (36.16 billion Tomans). Regarding the total cost (summation of M&R and CO_2 costs), the sustainable model outperforms the conventional model since the total cost of the sustainable model (114.62 billion Tomans) is 1.1% less than the conventional model (115.89 billion Tomans).

In addition, the maximum and minimum annual budget fluctuations in both approaches were less than 25%. Since most highway agencies cannot provide the budget with high fluctuation, the mentioned constraint increases the model's applicability. As can be perceived, the annual cost volatility is low in both models due to the budget fluctuation constraint.

Insert Figure 3 Here

5.4. Environmental impacts

CO_2 emission is a pernicious greenhouse gas emission deteriorating the environment (Ghavami et al., 2021). As previously mentioned, the transportation industry is the second largest source of GHG pollution globally (Ang & Marchal, 2013); therefore, reducing CO_2 emissions is crucial for highway agencies. For this purpose, the CO_2 emission minimisation was considered as the objective function for the sustainable model. As can be seen in Figure 4, the sustainable model reduced CO_2 emissions by 6.5%, demonstrating superior performance over the conventional model. Due to the limited capacity of the environment, annual CO_2 emissions should be controlled to a limited amount (Nikolaou & Tsalis, 2018). According to the optimisation models, the budget fluctuation was controlled in both models, which reduced variations in annual CO_2 emissions. The sustainable and conventional models emitted 20.46 and 21.87 million kg CO_2 in the planning horizon, respectively, while yielding similar IRIs in the network during the final year of the planning horizon.

Insert Figure 4 Here

5.5. Social aspects

As mentioned, two parameters, including equity and safety indices, were applied to evaluate the effectiveness of the sustainable model. The equity level in the pavement network was evaluated during the fifth year of the analysis, which was determined to be 0.408 and 0.574 in the sustainable and conventional models, respectively. As mentioned, the amount of equity is decreased by increasing the value of the equity index. Consequently, the sustainable model demonstrated better performance than the conventional model. Due to the presence of $AADT$ in Equation (12), the high-traffic sections were in better condition than the low-traffic ones at the end of the analysis period. By applying the sustainable model, the sense of well-being and welfare is increased in society greatly, while people's dissatisfaction is significantly reduced.

Moreover, the safety index of the sustainable and conventional models was 183.79 and 188.31. A reduction in the safety index leads to reducing the number of crashes, and as a result, improves safety. Although the sustainable model concentrated more on pavement sections with higher $AADT$ to minimise the number of crashes during the analysis period, the safety index was only reduced by 2.5%. This low reduction resulted from allocating more budget to the first and second years in the conventional model and a slightly outperforming conventional model to reduce IRI in the first and second years of the analysis period. To conclude, the sustainable model can slightly outperform the conventional model in terms of safety increment.

5.6. Comparison of the treatments of both models

This study aimed to plan M&R treatments for a large-scale network of primary roads, including 110 flexible pavement sections. The planning horizon for the mentioned pavement network was considered for a 5-year period. Moreover, a type of treatment should be assigned to each section in each year. As a result, 550 decisions had to be made for the mentioned pavement network during the planning period. The number of each treatment ID in each year is represented in Tables 3 and 4. In Table 3, the number of each treatment ID in each year for the sustainable model is indicated. Besides, the number of each treatment ID in each year for the conventional model is represented in Table 4. For instance, the numbers of the first column of Table 3 were explained to clarify these numbers. In this regard, treatment ID 1 (do nothing) was planned for 43 sections in the first year by the sustainable model. In addition, treatment ID 2, which was preventive maintenance type 1, was scheduled for 25 sections in the first year of evaluation in the sustainable model. Moreover, treatment ID 3 was planned to be applied to two pavement sections in the first year of planning horizon by the sustainable approach. Additionally, treatment ID 4, which was light rehabilitation, was scheduled to be implemented on 38 pavement sections in the first year of analysis in a sustainable manner. Furthermore, the highway agency should apply the medium rehabilitation, which was treatment ID 5, on two pavement sections in the first year of planning by the sustainable method. Besides, no pavement section needed heavy rehabilitation, which was treatment ID 6, in the first year of evaluation in the sustainable strategy.

As indicated, the conventional model used treatment ID 5 and 6 more than the sustainable model. The heavy rehabilitation improved the IRI of the sections significantly, and it could be appropriate for sections in poor condition (e.g., a section with an IRI of 6.93), but environmental pollutions notably increased. In this regard, the sustainable model rarely employed treatment ID 6 (heavy rehabilitation). On the other hand, the sustainable model approached to select the treatment ID 2, which was more efficient in order to reduce the environmental emissions. Meanwhile, the number of selected treatment ID 2 was much higher than that of ID 3 in both models, particularly the sustainable model. As previous studies concluded, crack sealing is an environmentally-friendly treatment (Naseri et al., 2021) and offers the appropriate preventive maintenance to improve sustainability, while slurry seal is proper preventive maintenance to enhance IRI. The analysis of M&R treatments reveals that the M&R treatments must be optimally and appropriately selected to enhance sustainability. Due to the constraints of the optimisation models, the models were prevented from applying the M&R treatments for two consecutive years. Because the initial condition of the sections was inauspicious, both models applied more treatments at the beginning of the planning horizon.

Insert Table 3 Here

Insert Table 4 Here

6. Conclusion

The current study aimed to establish M&R treatment plans for a large-scale pavement network with much focus on sustainability in the M&R scheduling. To this end, two optimisation models were utilised to optimise the pavement M&R scheduling: including sustainability and conventional models. A novel sustainability index, which includes highway agency cost, CO_2 emissions, and a social index, was introduced to generate the sustainability model. A powerful metaheuristic algorithm, named Marine Predator Algorithm (MPA), is adjusted to solve the M&R scheduling optimisation problem.

The results indicate that both models continuously enhanced the IRI of the network and reached almost the same value in the final year. Therefore, the performance of the models is deemed acceptable in reducing the IRI of the network. The sustainable model has a higher M&R cost than the conventional model and applying the sustainable model can increase the M&R cost by roughly 1.3%. However, the CO_2 cost of the sustainable model is 6.5% less than the conventional model. Considering both M&R cost and CO_2 cost indicates that sustainable model can reduce the total cost by 1.1%.

In terms of environmental impacts, the sustainable model performed better than the conventional model, producing 1.4 million kg (6.5%) less CO_2 emission during the analysis period. Therefore, the sustainable model is more eco-friendly than the conventional model. Applying the equity index resulted in nearly the same condition of pavement sections. In addition, the sense of well-being, welfare, and justice in society were enhanced. Applying the equity index of the pavement network as the objective function of the sustainable model reduced the equity index by 40.7% compared to the conventional approach. This means that the equity of the sustainable model was 40.7% greater than the conventional model in the final year of the scheduling. Moreover, employing the safety index in the modelling resulted in a reduction in the safety index by 2.5%. Therefore, applying the sustainable model instead of the conventional one could reduce the number of crashes by 2.5%.

The analysis of the preventive treatments reveals that the sustainable model tends to select crack sealing due to its lower cost and environmental impacts, while the conventional model elects light rehabilitation because of its high IRI reduction-cost ratio. The conventional model chooses the medium and heavy rehabilitation more than the sustainable model because heavy rehabilitation remarkably enhances the IRI of the pavement, and it is cost-effective for pavements with very poor conditions.

Ultimately, it is pertinent to emphasise that both models achieved the same IRI of the network in the final year of the analysis, where the CO_2 emission of the conventional model were reduced by the sustainable model. Furthermore, the sustainable model also achieved lower equity and safety indices compared to the conventional model. Nonetheless, the agency cost of the sustainable model was 1.1% higher than that of the conventional model.

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Tables' captions

Table 1. The IRI improvement, cost, and CO_2 emission of each M&R treatment.

Table 2. The statistical comparison of sustainable and conventional models' results.

Table 3. The treatments selected by the sustainable model.

Table 4. The treatments selected by the conventional model.

Table 1. The IRI improvement, cost, and CO_2 emission of each M&R treatment.

ID	Treatment	M&R actions	IRI improvement (m/km)	Unit cost (Toman/m^2)	Unit CO_2 (kg/m^2)
1	Do nothing		0	0	0
2	Preventive maintenance type 1	Crack sealing	0.16	3000	0.27
3	Preventive maintenance type 2	Slurry seal	0.23	5000	1.37
4	Light rehabilitation	Surface milling, 4-6 cm HMA overlay	1.2	15000	4.13
5	Medium rehabilitation	milling, 8-12 cm HMA overlay	2	32000	8.26
6	Heavy rehabilitation	Replacement of the entire existing pavement structure	The condition of the corresponding pavement changes to a new pavement condition, $IRI_{new} = 1.5$	65000	21.31

Table 2. The statistical comparison of sustainable and conventional models' results.

Objective function value	Sustainable model	Conventional model
Minimum	0.801	7.758E14
Maximum	0.995	8.096E14
Average	0.891	7.931E14
Standard deviation	0.048	9.605E12
Standard error	0.009	1.754E12
Kurtosis	-0.017	-1.001

Table 3. The treatments selected by the sustainable model.

Treatment ID	First year	Second year	Third year	Fourth year	Fifth year	Sum
1	43	64	48	69	62	286
2	25	12	18	13	16	84
3	2	4	5	2	2	15
4	38	29	37	25	28	157
5	2	0	1	1	2	6
6	0	1	1	0	0	2

Table 4. The treatments selected by the conventional model.

Treatment ID	First year	Second year	Third year	Fourth year	Fifth	Sum
1	44	74	55	67	71	311
2	16	1	11	12	7	47
3	6	1	4	4	1	16
4	41	32	38	24	29	164
5	2	1	2	3	1	9
6	1	1	0	0	1	3

Figures' captions

Figure 1. The steps adopted in this study.

Figure 2. The annual average IRI of the network.

Figure 3. The annual budget allocation of models.

Figure 4. The annual CO_2 emissions.

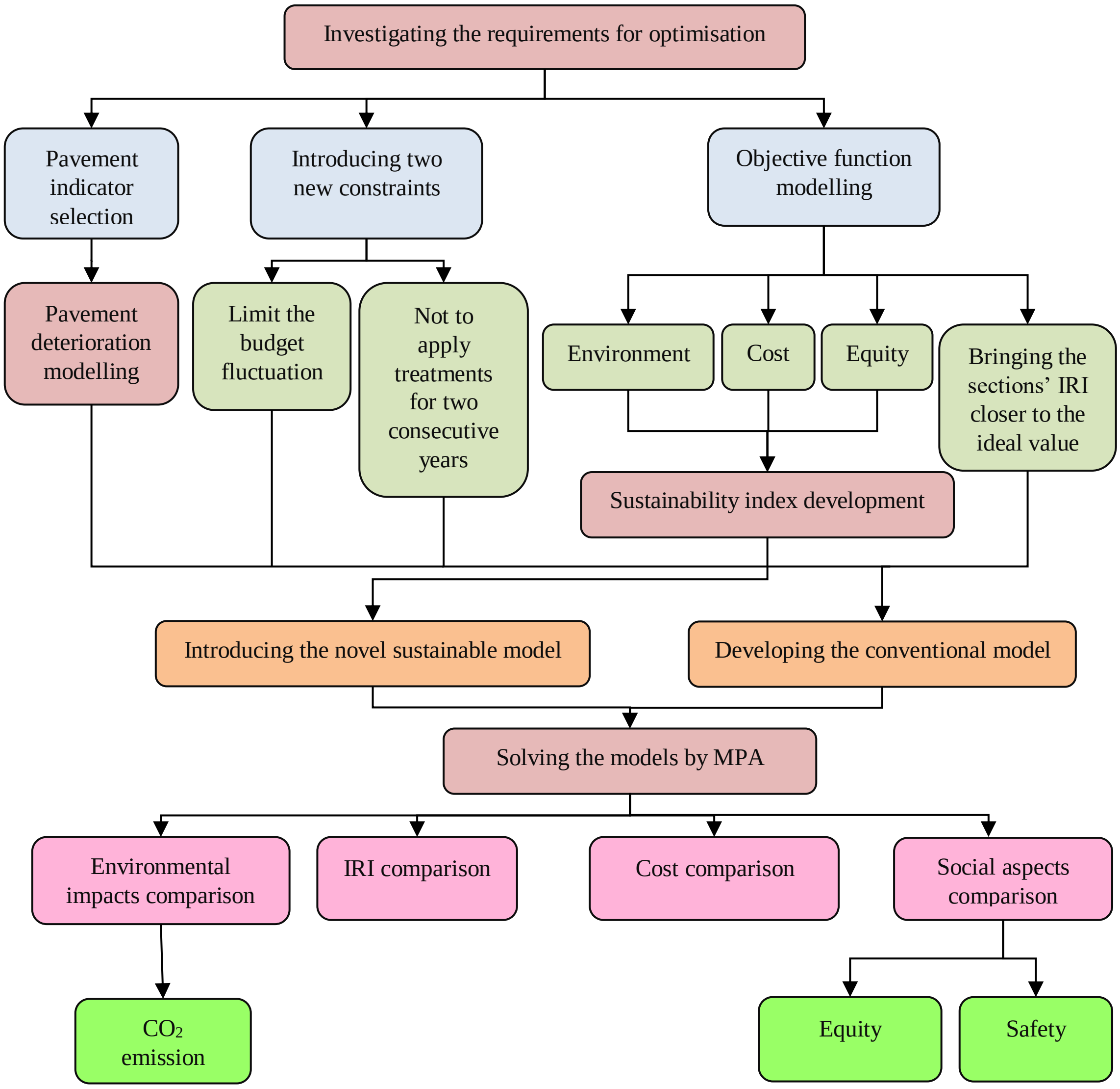

Figure 1. The steps adopted in this study.

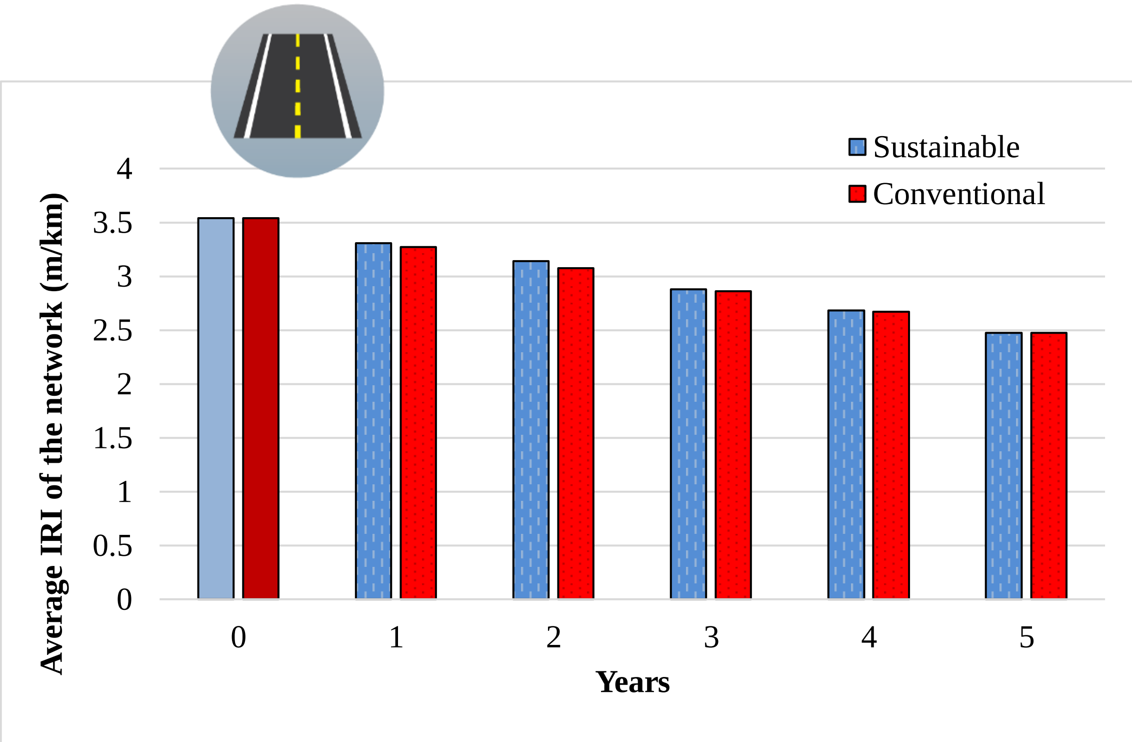

Figure 2. The annual average IRI of the network.

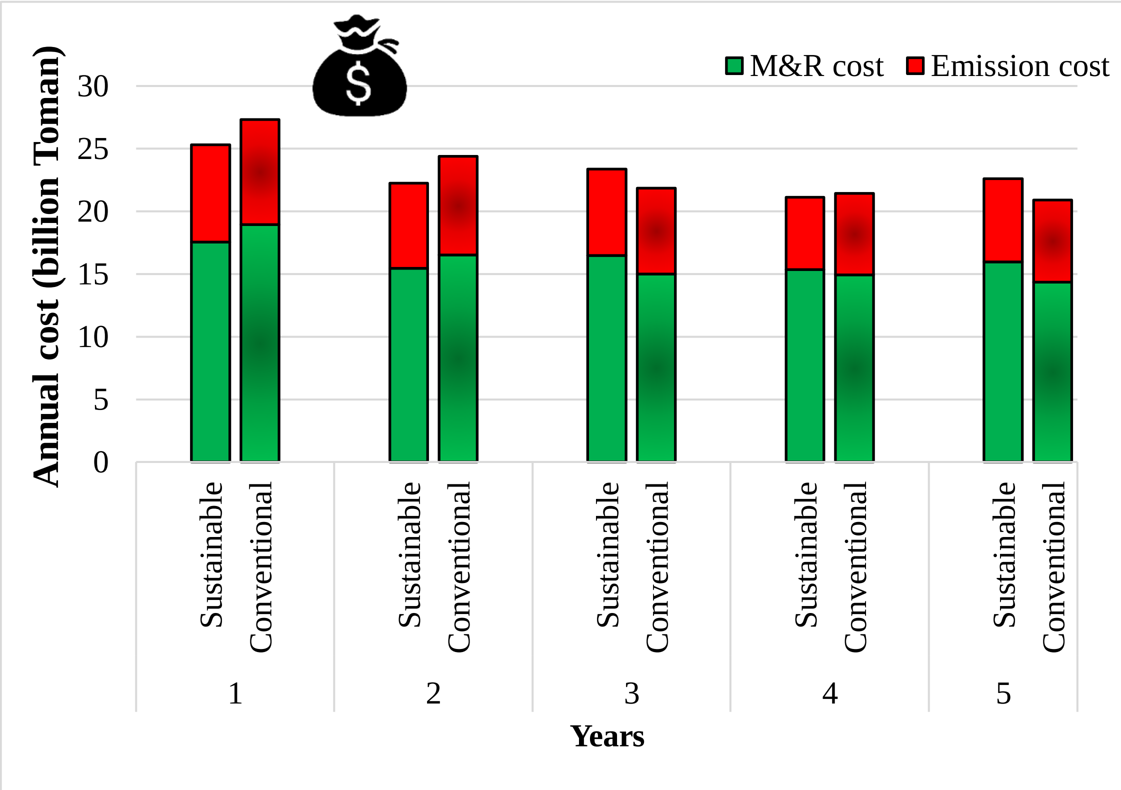

Figure 3. The annual budget allocation of both models.

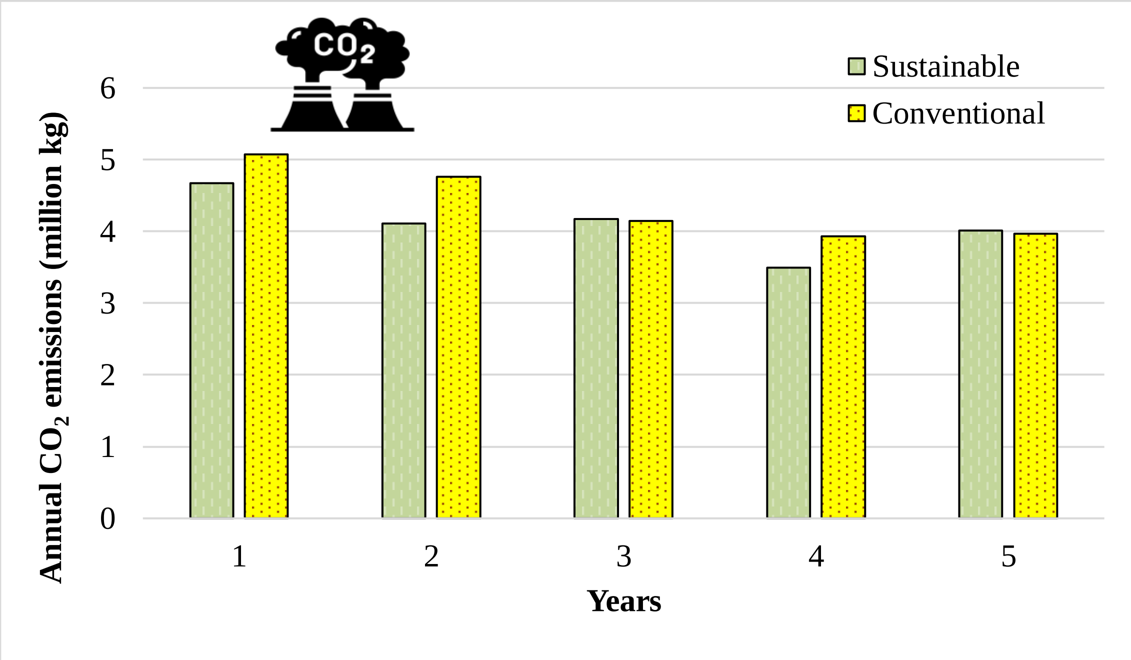

Figure 4. The annual CO_2 emissions.