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A multi-objective differential evolutionary algorithm for optimal sustainable pavement maintenance plan at the network level

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ABSTRACT

Sustainable highway pavement maintenance is important for achieving sustainability in the transportation sector. Because the three aspects included in sustainability metrics (environment, economy, and society) often contradict each other, maximising the sustainability performance of highway pavements is difficult, especially at the network level. This study developed a novel multi-objective heuristic algorithm to formulate sustainable highway pavement network maintenance plans considering carbon emissions (CE), life cycle agency cost (LCAC), and pavement long-term performance (LTP). The proposed algorithm is a new variant of multi-objective differential evolution (MODE) that incorporates self-adaptive parameter control and hybrid mutation strategies embedded in its framework (MOSHDE). Three state-of-the-art multi-objective heuristics, namely, the non-dominated sorting genetic algorithm II(NSGA-II), classic MODE, and multi-objective particle swarm optimisation (MOPSO), as well as the proposed MOSHDE, were applied to an existing highway pavement network in China for performance evaluation. Compared with other heuristic algorithms, the proposed self-adaptive parameter control strategy enables the automatic adjustment of the control parameters, avoiding the time-consuming process of selecting them and enhancing the robustness and applicability of differential evolution. The hybrid mutation strategy uses both exploration and exploitation operators for the mutation operations, thus leveraging both global and local searches. The results of the numerical experiment demonstrate that MOSHDE outperforms the other tested heuristics in terms of efficiency and quality and diversity of the obtained approximate Pareto set. The optimal solutions obtained by the proposed method correspond to a proactive maintenance policy, as opposed to the reactive maintenance policy commonly adopted in current practice. In addition, these solutions are more cost-effective and environmentally friendly and can provide better pavement performance to highway users over the project life cycle. Therefore, the proposed MOSHDE may help practitioners in the transportation sector make their highway infrastructure more sustainable.

1. Introduction

Highways are essential infrastructure for any country because they make a significant contribution to economic and social development (Xu et al., 2021). With the ever-increasing availability of paved highway networks, users are likely to demand better services in terms of efficiency, quality, comfort, and safety (Zhang and Mohsen, 2018). However, highway pavements inevitably deteriorate over time owing to repeated loading and adverse climatic conditions. Therefore, highway operators must conduct regular maintenance tasks to maintain pavement network serviceability. However, the current situation is concerning. For instance, in the US, 43% of public roads are in poor or mediocre conditions, a figure that has been increasing in recent years (ASCE, 2021). One reason for this phenomenon is that the budgets of highway agencies are often limited and cannot meet the requirements for pavement maintenance (Naseri et al., 2021). Many highway agencies have adopted reactive maintenance policies where intensive maintenance programs are implemented to rehabilitate pavements already under poor conditions. Unfortunately, because these rehabilitation programs are generally costly, they are often postponed due to a shortage of funds. Many studies have demonstrated that delays in maintenance activities can lead to a severe deterioration in pavement conditions and result in additional future costs, widening even more the gap between the required maintenance funds and the available budget

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(Mohamed et al., 2022; Zhang and Mohsen, 2018). Instead of adopting a reactive policy, recognizing that preventive treatments are cheaper and pavements in good condition deteriorate at a slower rate, these studies suggest that highway operators adopt proactive policies to service paved roads while they are still in good condition. Therefore, there is an urgent need for highway managers to find cost-effective strategies for maintaining pavement networks in serviceable conditions.

On the other hand, pavement maintenance activities may have adverse environmental effects (Nalbandian et al., 2022). For instance, maintenance activities consume large amounts of bitumen and aggregates, and require the intensive operation of construction equipment. Sourcing these construction materials and supporting equipment operations lead to enormous amounts of greenhouse gas emissions, which are a critical cause of the emerging climate change (Huang et al., 2021). According to statistics, highway construction and maintenance projects in the US require more than 300 million tons of construction materials per year (Chen et al., 2022), and in China, the road sector is predicted to produce approximately 1100 million tons of CO_2 by 2030 (Shang et al., 2010). Therefore, decision-makers should adopt more environmentally friendly policies in pavement management to mitigate these factors.

Generally, a good maintenance program should guarantee that the pavement performs adequately during its life cycle, providing users with better service at an acceptable cost while minimising its environmental impacts. These requirements reflect the need to account for the three bottom lines of sustainability (environment, economy, and society) in the transportation sector (Bueno et al., 2015). At the network level, transportation managers should devise sustainable maintenance plans that schedule the pavement section to treat, the maintenance treatment to apply, and the time of implementation within the project life cycle (Gao et al., 2012). Such plans should be assessed in terms of the three sustainability aspects to maximise their overall effectiveness (Santhanam and Gopalakrishnan, 2013; Santos et al., 2019). Sustainability could include several objectives, such as reducing environmental effects, limiting costs, and enhancing pavement conditions, which indicate the serviceability delivered to users (Torres-Machi et al., 2017). However, some of these objectives compete against one another. For example, a cost reduction may lead to poor pavement conditions. Hence, multi-objective optimisation (MOO) arises as the best alternative to simultaneously meet all objectives (Hashemi, 2021).

MOO can be addressed from both mathematical and heuristic approaches. In previous studies, both methods were applied to address the pavement network maintenance optimisation problem (PNMOP). Mathematical approaches can only deal with problems modelled through objective functions that are differentiable or continuous or contain convex decision variables. PNMOP is a nondeterministic polynomial-time hard (NP-hard) problem, as there are $T^{Y \times N}$ possible solutions for a pavement network with N sections and T available treatments to implement over a planning period of Y years (Yepes et al., 2016). Although mathematical programming can find an accurate optimal solution, its execution time increases exponentially along with the problem complexity; thus, it is mainly applied to problems with low complexity, such as project-level problems (Gao and Zhang, 2013; Gomes Correia et al., 2021; Huang et al., 2021) and single-objective optimisation (de la Garza et al., 2011; Gao et al., 2012; Medury and Madanat, 2013).

As opposed to mathematical approaches, heuristics can efficiently deal with most of the difficulties of multi-objective NP-hard problems, as it uses a population of solutions, namely individuals, that perform exploitation or exploration to search for the Pareto-optimal set through a number of iterations (Donev and Hoffmann, 2018). Exploitation refers to a local search that aims to find an optimal result in a neighbouring space or otherwise move from a current position to a better neighbourhood (Yi et al., 2014), whereas exploration focuses on a global search beyond the local search space (Tsang and Voudouris, 1997). Extensive studies that have applied exploration to solve the PNMOP can be found, and among them, the genetic algorithm (GA) (Deb et al., 2002) and particle swarm optimisation (PSO) (Coello and Lechuga, 2002) method are the most frequently used techniques.

Lu and Tolliver (2013) presented a MOO of the PNMOP that employed a GA to search for optimal solutions leading to minimum maintenance costs and average network roughness considering climatic factors. One of the variants of GA, the non-dominated sorting genetic algorithm (NSGA-II), was developed by Khavandi Khiavi and Mohammadi (2018) to address a tri-objective PNMOP that considered maintenance costs, user costs, and the residual value of pavement in the end-of-life stage. A similar study was conducted by Cao et al. (2020), in which NSGA-II was applied to solve the PNMOP accounting for maintenance costs and environmental factors. Another MOO was proposed by Guan et al. (2022), where NSGA-II was modified with mixed population initialisation for a well-distributed Pareto front to solve the trade-offs between agency costs, user costs, and environmental impacts, considering the dynamic traffic responses of road users and the interdependencies between road links. GA indisputably has strong adaptability owing to its free coding approach, for example, binary-coded and real-coded GA (Chen and Zheng, 2021). However, previous studies have reported severe limitations of the GA, including the high possibility of it producing duplicate individuals, which makes it challenging to find isolated solutions (Fang et al., 2018), and premature convergence because of its high dependence on the quality of the individuals (Pavez-Lazo and Soto-Cartes, 2011).

The multi-objective particle swarm optimisation (MOPSO) algorithm was applied by Chou and Le (2011) to address trade-offs between cost and reliability over the pavement life cycle, and by Ahmed et al. (2018) and Mahmood et al. (2018) to minimise maintenance costs while maximising the pavement health. The original PSO algorithm addresses continuous optimisation problems. However, most parameters involved in PNMOP are naturally discrete, for example, year, pavement section, and maintenance decision, which calls for a transformation from continuous coding to discrete coding. Consequently, the quality of the solutions highly depends on the effect of this transformation (Chen and Zheng, 2021).

Although most studies focus on exploration Yepes et al. (2016) proposed using the hybrid greedy randomised adaptive search procedure (GRASP), which applies an exploitation heuristic, to determine the optimal pavement maintenance plan with the maximum long-term effectiveness (LTE) constrained to a defined budget and minimum pavement condition. A similar approach was adopted by Torres-Machi et al. (2017) to minimise greenhouse gas emissions while maximising the LTE of the maintenance plan under defined budget constraints. In this study, the environmental impact was considered as a penalty to LTE, and thus, the bi-objective problem was converted to a single objective. Santos et al. (2017) presented a modified NSGA-II that uses a hybrid search strategy that integrates both exploration and exploitation operators to solve a tri-objective PNMOP.

Despite the multiple contributions that previous studies have made, some limitations persist. First, most studies apply GA or PSO to solve the PNMOP, but more advanced heuristics with better performance in addressing practical issues are almost neglected. Monsef et al. (2019) compared the performance of NSGA-II, MOPSO, and a novel multi-objective differential evolution (MODE) heuristic algorithm for designing a water distribution network, finding that MODE was better than the other two in terms of convergence speed and inverted generational distance, which is a metric that evaluates the performance of a multi-objective heuristic. Another study on power system optimisation indicates that MODE can generate more diverse individuals than several other multi-objective heuristics (Deb et al., 2014) and, due to such a more diverse population, has a greater probability of obtaining more optimal solutions.

Second, the performance of many heuristics heavily relies on the appropriate tuning of the control parameters, for example, the crossover and mutation rates in GA, or the inertia weight and learning factors in PSO, which are commonly determined based on empirical tests and practical experience. This may reduce the efficiency and applicability of the algorithms, as the empirical test is time-consuming and an appropriate performance under the set parameters cannot be guaranteed. Therefore, more reliable selection strategies for control parameters are required.

Third, many studies only perform exploitation or exploration in the optimisation process. Exploitation uses individuals in the current population to achieve the best effect, whereas exploration finds new better individuals. Therefore, instead of applying one of them in the iterations, a hybrid search strategy that assigns individuals with better performance to exploitation and those with worse performance to exploration to maintain a balance between global and local searches is more desirable. However, only one study has considered this option (Santos et al., 2017).

Considering the limitations identified above, a new MOO heuristic algorithm was developed in this study to solve the PNMOP incorporating sustainable objectives. This new algorithm is a novel variant of MODE that includes self-adaptive control parameters and hybrid mutation operators, hence named MOSHDE. To enhance the searching ability of MODE and avoid its sensitivity to control parameters, MOSHDE categorises individuals into two groups to process the self-adaptive control parameters and hybrid mutation operators embedded in its framework. To verify the effectiveness of the developed heuristic, its performance was compared with those of NSGA-II, classic MODE (CMODE), and MOPSO.

2. MOO for sustainable highway pavement maintenance

2.1. Pareto optimality

When dealing with MOO problems, the objectives often compete against one another. Thus, it is nearly impossible to simultaneously obtain an optimal solution for all objectives. Instead, the goal of MOO is to find a number of optimal solutions in terms of Pareto optimality (Afshari et al., 2019).

The Pareto-based approach aims to balance a trade-off between different objectives, denoted as $F_1, F_2, \ldots, F_K$. Let the objective problem be denoted by $\boldsymbol{F}(\boldsymbol{X}) = [F_1(\boldsymbol{X}), F_2(\boldsymbol{X}), \ldots, F_K(\boldsymbol{X})]$, where $\boldsymbol{X}$ is a vector of the variables that should be considered and $F_k(\boldsymbol{X})$ $(k = 1, \ldots, K)$ is the kth objective function. A Pareto dominance relation $\prec$ can be defined for a pair of solutions $\boldsymbol{X_1}$ and $\boldsymbol{X_2}$, $\boldsymbol{X_1} \prec \boldsymbol{X_2}$ ($\boldsymbol{X_1}$ dominates $\boldsymbol{X_2}$) if $F_k(\boldsymbol{X_1}) \le F_k(\boldsymbol{X_2})$ for all $k \in [1, K]$, and $F_k(\boldsymbol{X_1}) < F_k(\boldsymbol{X_2})$ for at least one k. If $F_k(\boldsymbol{X_1}) < F_k(\boldsymbol{X_2})$ and $F_l(\boldsymbol{X_1}) > F_l(\boldsymbol{X_2})$ for at least one pair $k \ne l$, then none are dominated by the other. This non-dominance relationship determines Pareto optimality. If no $\boldsymbol{X}$ dominates $\boldsymbol{X}^*$, then $\boldsymbol{X}^*$ is called a Pareto-optimal solution. Such a solution cannot be further optimised in any of the objectives without compromising the performance of another. The set of all non-dominated solutions, known as the Pareto-optimal set, is the solution of the problem, and the objective function values of all Pareto-optimal solutions in the objective space are the Pareto front. Therefore, the main goal of MOO is to search for a Pareto-optimal set. Given that this task is too computationally expensive, multi-objective heuristics are commonly employed to search for a solution set as close to the Pareto front as possible, which is called the Pareto front approximation (Afshari et al., 2019; Sheng et al., 2013).

2.2. Model formulation

The formulation of the MOO model to solve the PNMOP in this study includes the following: (1) identification of parameters needed, (2) definitions of the objective functions, and (3) definition of the constraints.

As shown in Fig. 1, the solution is a $Y \times N$ matrix, $X = \{x_{y,n}\}_{Y\times N}$, where each element $x_{y,n}$ represents a treatment to be applied at pavement section n on year y.

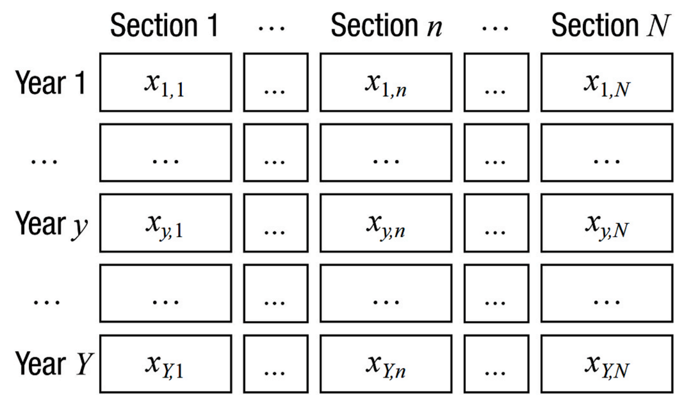


Fig. 1. The form of the solution to the PNMOP.

2.2.1. Parameters

The parameters are the input data of the optimisation model and include the number of pavement sections, section lengths, initial pavement conditions, and expected pavement deterioration curve. They also include other technical data, such as available maintenance treatments to address pavement defects, service life, application scope, unit costs, and environmental impacts. When considering the treatment costs in different years, it is important that the effect of inflation on both the industrial production cost and the value of money be considered because a pavement can be in service for tens of years.

The pavement conditions can be assessed by the pavement condition index (PCI) (Yu et al., 2017), which is computed as:

$$PCI = 100 - 15DR^{0.412} \tag{1}$$

where DR refers to the distress ratio of the pavement including cracking, potholes, and rutting. The PCI ranges between 0, corresponding to a wholly failed pavement, and 100, denoting a newly built one.

Pavements in better conditions can provide road users with better service and produce more benefits to society. Therefore, given a maintenance plan, its social benefit can be evaluated by the long-term pavement performance (LTP), which can be measured by the area bounded by the pavement condition curve and a set threshold (PCI_{min}) for each pavement section (Fig. 2). LTP is a popular replacement metric for user benefit because the area bounded by the PCI curve of a well-maintained pavement is greater than that of a poorly maintained pavement (Yepes et al., 2016).

The application of a maintenance treatment improves pavement conditions, thus extending the pavement service life. This extension can be used to assess the effectiveness of treatment. Moreover, maintenance treatments differ in terms of the defects they can address; therefore, their

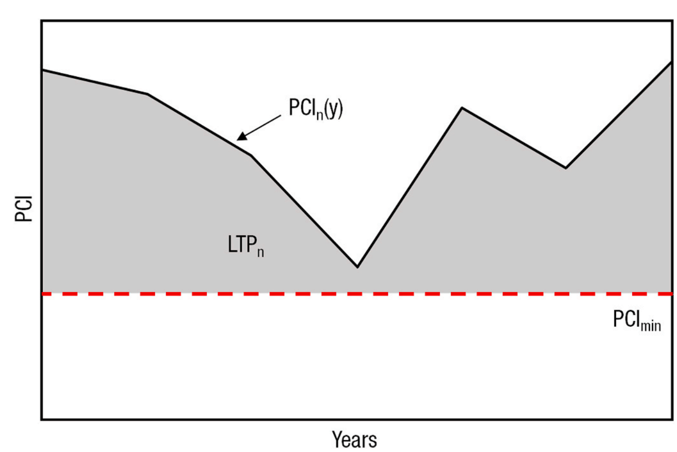


Fig. 2. Long-term performance (LTP) of section n.

application scopes differ (expressed as PCI). These scopes can be defined based on the technical guidance and specifications used by the transport administration to select the appropriate treatments.

Environmental impacts are evaluated in terms of embodied carbon emissions (CE), as they are the primary trigger of global warming (IPCC, 2014). In this study, the CE of each treatment is computed according to the step-by-step method proposed by Giustozzi et al. (2012), which considers the CE due to materials, transportation, and on-site work.

2.2.2. Objective functions and constraints

To realise the main goal of sustainable pavement maintenance, objective functions must be defined for each of the three competing bottom lines of sustainability, namely, environment, economy, and society. Thus, the following objectives were defined: (1) minimise life cycle CE, (2) minimise life cycle agency cost (LCAC), and (3) maximise the social benefit of the pavement. For a given solution $\boldsymbol{X_i} = \{x^i_{y,n}\}_{Y\times N}$, these objective functions can be expressed as follows:

$$\min F_1 = \min\left(\sum_{n=1}^{N}\sum_{y=1}^{Y}\left(CE_{x^i_{y,n}} \times W_n \times L_n\right)\right) \tag{2}$$

$$\min F_2 = \min\left(\sum_{n=1}^{N}\sum_{y=1}^{Y}\left(C_{x^i_{y,n}} \times W_n \times L_n\right)\right) \tag{3}$$

$$\max F_3 = \max\left(\sum_{n=1}^{N}\sum_{y=1}^{Y}\left(\frac{PCI_{x^i_{y,n}} + PCI_{x^i_{y+1,n}}}{2} \times W_n \times L_n\right)\right) \tag{4}$$

where F_1–F_3 denote CE, LCAC, and LTP of $\boldsymbol{X_i}$, respectively; N denotes the number of pavement sections; Y denotes the years of the analysis period; $x^i_{y,n} = 1, \ldots, T$ refers to the kind of treatment employed to service section n on year y; $CE_{x_{y,n}}$ and$C_{x_{y,n}}$ denote the unit CE and cost of treatment $x^i_{y,n}$, respectively; $PCI_{x^i_{y,n}}$ denotes the PCI value of section n on year y for solution $\boldsymbol{X_i}$, which is determined by a set deterioration pavement model and the effectiveness of the applied treatments; and W_n and L_n denote the width and length of section n, respectively.

Finally, the constraints considered in the MOO model are intended to guarantee the compliance of the solutions in terms of (1) pavement quality and (2) technical requirements. They are expressed as:

$$s.t. \quad PCI_{x^i_{y,n}} \geq PCI_{\min} \tag{5}$$

$$PCI_{x^i_{y,n}} \in \left[ASL_{x^i_{y,n}}, ASU_{x^i_{y,n}}\right] \tag{6}$$

where $PCI_{\min}$ is the minimal PCI value that should be guaranteed and $[ASL_{x^i_{y,n}}, ASU_{x^i_{y,n}}]$ is the application scope of treatment $x^i_{y,n}$.

The budget requirements are not considered in the optimisation procedure because the LCACs of most of the initial solutions are very high. Instead, we used it as a standard to select feasible solutions from the approximate Pareto front obtained.

Equations (2)–(4) are the objective functions used to obtain the approximate Pareto front. Equation (5) indicates the pavement condition constraint, which means that the PCI value of any pavement section should always be higher than a set value. Equation (6) states the technical constraints in terms of the applicability of the treatments, meaning that a treatment is not applicable if the pavement condition is outside its application scope.

2.3. Optimisation algorithms

2.3.1. NSGA-II

Deb et al. (2002) developed NSGA-II for MOO, which combines a GA with nondominated sorting. In NSGA-II, descendants are generated through selection, crossover, and mutation operations, and the population of the new generation is selected through non-dominated sorting and crowding distance comparison.

Non-dominated sorting is an operation that sorts individuals within a population into different Pareto fronts according to dominance relationships (Deb et al., 2002), which is a significant process for selecting individuals for the next generation in many multi-objective heuristics. Taking as an example a population $\boldsymbol{P}$ with NI individuals, first, the Pareto-optimal set in $\boldsymbol{P}$ is sorted to the first Pareto front, denoted as $\boldsymbol{PF_1}$, and then the Pareto-optimal set with the remaining individuals $\boldsymbol{P} - \boldsymbol{PF_1}$ is sorted to the second Pareto front, denoted as $\boldsymbol{PF_2}$; this process is repeated until the whole population $\boldsymbol{P}$ is sorted. A critical property of the population sorted by non-dominated sorting is that individuals belonging to $\boldsymbol{PF_k}$ are dominated by at least one individual belonging to $\boldsymbol{PF_j}$ $(1 \leq j < k \leq n)$.

The crowding distance represents the closeness of a non-dominated solution to other solutions (Schardong et al., 2013). The crowding distance of an individual indicates the density of the other individuals surrounding that individual. Within the same Pareto front, a solution with a greater crowding distance is often preferable because a less crowded population has more diverse individuals. In NSGA-II, the parents and their descendants are ranked considering Pareto seniority and crowding distance to select the top NI individuals that will form a new generation.

In this study, we use a real-coded NSGA-II framework to obtain the Pareto front approximation of the target problem.

2.3.2. MODE

Storn and Price (1997) originally developed the differential evolution (DE) algorithm. Owing to its efficiency, robustness, and simplicity, DE has been widely applied to various engineering problems that are non-linear and multi-constrained (Dong et al., 2012; Mansouri et al., 2015). In DE, for each initial population denoted as $\boldsymbol{P}$ in different generations, three randomly selected and mutually different individuals are used to produce a mutation vector using the following mutation equation:

$$\boldsymbol{V_i} = \boldsymbol{X_{r3}} + F \times (\boldsymbol{X_{r1}} - \boldsymbol{X_{r2}}) \tag{7}$$

where $\boldsymbol{X_{r1}}$, $\boldsymbol{X_{r2}}$, and $\boldsymbol{X_{r3}}$ are different random individuals from $\boldsymbol{P}$; $\boldsymbol{V_i} = \{v^i_{y,n}\}_{Y\times N}$ is the mutation vector; and F is the mutation factor, which is a constant recommended to be between 0 and 1. To generate a crossover vector, $\boldsymbol{U_i} = \{u^i_{y,n}\}_{Y\times N}$, the crossover operator is used as follows:

$$u^i_{y,n} = \begin{cases} v^i_{y,n} & \text{if } rand(0,1) < CR \text{ or } y = r \\ x^i_{y,n} & \text{otherwise} \end{cases} \tag{8}$$

where CR is the crossover rate, which is a constant between 0 and 1.

To determine whether vector $\boldsymbol{U_i}$ should survive to the next generation (denoted as $G+1$), it should be compared with the corresponding individual $\boldsymbol{X_i}$ from the current generation (the G-th generation), denoted as $\boldsymbol{X_i^G}$. Then, the individual of the next generation, $\boldsymbol{X_i^{G+1}}$, can be chosen using Equation (9):

$$\mathbf{X_i^{G+1}} = \begin{cases} \boldsymbol{U_i} & \text{if } \boldsymbol{U_i} \text{ dominates } \boldsymbol{X_i^G} \\ \boldsymbol{X_i^G} & \text{otherwise} \end{cases} \tag{9}$$

In the past few years, researchers have attempted to expand DE to deal with MOO problems, and MODE has turned out to be a fascinating alternative to these issues (Monsef et al., 2019). This study used classic MODE (CMODE) for comparative testing. However, instead of using Equation (9) to select individuals in the next generation, non-dominated sorting and crowding distance ranking are used to select new individuals, similar to NSGA-II.

2.3.3. MOPSO

Inspired by bird herd behaviour, Kennedy and Eberhart (1995) developed the particle swarm optimisation (PSO) algorithm, in which swarm intelligence is applied to find optimal solutions. In the PSO algorithm, individuals are represented by particles that move towards the optimal solution with a velocity controlled by the velocity of the same individual in the last generation (inertia), personal guides (the distance to the optimal position of the same individual in previous generations), and global guides (the distance to the position of the leader, which has the best performance in the optimisation process) (Monsef et al., 2019).

Coello and Lechuga (2002) expanded PSO to solve MOO problems, in which an external repository was used to archive non-dominated particles, and the leader was randomly chosen from the repository using a roulette wheel selection method. Coello et al. (2004) further modified MOPSO to improve its performance by applying a mutation operation after updating the particle positions. Here, MOPSO of Coello et al. (2004) was performed.

2.3.4. The proposed MOSHDE

This study proposed a new variant of MODE with self-adaptive control parameters and hybrid mutation operators, namely, MOSHDE, as shown in Fig. 3.

In the initialisation process of the proposed approach, each individual is assigned a pair of control parameters: F and CR. The values of the assigned parameters were random numbers between zero and one. The individual then produces a crossover vector with the assigned control parameters and a specific mutation operator. Because control parameters determine the step size of the iteration, and better control

Algorithm MOSHDE

Generate the initial population denoted as $\boldsymbol{P} = \{\boldsymbol{X}_1,\dots,\boldsymbol{X}_{NI}\}$, $\boldsymbol{X}_i = \{x^i_{y,n}\}_{Y\times N}$, NI denotes the number of individuals in the population.
Generate mutation and crossover parameters F and CR for each individual with $F_i = rand(0,1)$, $CR_i = rand(0,1)$
Define the mutation set $\boldsymbol{VS}$ and crossover set $\boldsymbol{US}$, $\boldsymbol{VS} = \{\boldsymbol{V}_1,\dots,\boldsymbol{V}_{NI}\}$, $\boldsymbol{V}_i = \{v^i_{y,n}\}_{Y\times N}$, $\boldsymbol{US} = \{\boldsymbol{U}_1,\dots,\boldsymbol{U}_{NI}\}$, $\boldsymbol{U}_i = \{u^i_{y,n}\}_{Y\times N}$
Evaluate the objective functions for each individual in $\boldsymbol{P}$
Rank these individuals through non-dominated sorting and crowding distance comparison
while $G <$ Max$G$ **do**
for $i = 1$ to NI **do**
    select three mutually different individuals $r1 \neq r2 \neq r3 \neq i$

$$V_i = \begin{cases} X_{r1} + F_i \times (X_{r2} - X_{r3}) & \text{if } \operatorname{rank}(X_i) \geq \xi \\ X_i + F_i \times (X_1 - X_i) + F_i \times (X_{r2} - X_{r3}) & \text{otherwise} \end{cases}$$

end for
for $i = 1$ to NI **do**
    $r = rand(1,Y)$
    for $y = 1$ to Y **do**
        for $n = 1$ to N **do**

$$u^i_{y,n} = \begin{cases} v^i_{y,n} & rand(0,1) < CR(i) \quad \text{or} \quad y = r \\ x^i_{y,n} & \text{otherwise} \end{cases}$$

        end for
    end for
end for
for $i = 1$ to NI **do**
    Use Equations (5) and (6) to check the feasibility of $\boldsymbol{U}_i$
    if feasibility check fails **then**
    $\boldsymbol{U}_i = \boldsymbol{X}_i$
    end if
end for
Evaluate the objective functions of each $\boldsymbol{U}_i$
Combine $\boldsymbol{P}$ and $\boldsymbol{US}$ into a candidate pool denoted as $\boldsymbol{CP}$
Rank the candidates in $\boldsymbol{CP}$ through non-dominated sorting and crowding distance comparison
for $i = 1$ to NI **do**
    if $Rank(\boldsymbol{X}_i) < Rank(\boldsymbol{U}_i)$ **then**
    $F_i = rand(0,1)$, $CR_i = rand(0,1)$
    end if
end for
Select the top NI individuals in $\boldsymbol{CP}$ as the new generation $\boldsymbol{P} = \{\boldsymbol{X}_1,\dots,\boldsymbol{X}_{NI}\}$
$G = G + 1$
end while
Select the non-dominated solutions with the LCAC less than the set budget in $\boldsymbol{P}$, which are the approximate Pareto solutions

Fig. 3. The pseudocode of MOSHDE.

parameters are more likely to generate better individuals, if the descendant ranks ahead of its parent vector in non-dominated sorting and crowding distance ranking, the values of the corresponding control parameters will be archived and used in the next generation.

As for the hybrid mutation strategy, both exploitation and exploration operators are employed to maintain a balance between global and local searches. In general, if the performance of an individual tends to be good in the current population, the exploitation operator should be assigned to it for better local search ability. However, if the individual has a significant possibility of poor performance, it should be assigned an exploration operator to enhance its global search ability.

2.3.4.1. Self-adaptive control parameters. The self-adaptive control parameters applied in the proposed MOSHDE enabled the algorithm to vary according to the problem. Furthermore, the feedback mechanism in the MOSHDE allows better control parameters to survive in the new generation with a greater possibility. For a given $\boldsymbol{X_i}$, the control parameters F_i and CR_i in the next generation are calculated as follows:

$$F_i^{G+1} = \begin{cases} rand(0,1) & \text{if } Rank(\boldsymbol{X}_i) \le Rank(\boldsymbol{U}_i) \\ F_i^G & \text{otherwise} \end{cases} \tag{10}$$

$$CR_i^{G+1} = \begin{cases} rand(0,1) & \text{if } Rank(\boldsymbol{X}_i) \le Rank(\boldsymbol{U}_i) \\ CR_i^{G+1} & \text{otherwise} \end{cases} \tag{11}$$

2.3.4.2. Hybrid mutation strategy. Among the different applicable mutation operators in DE, two are commonly used (Yi et al., 2014). The exploitation operator "DE/current-to-best/1″ is perfect for local search, which means that the best individual in the current generation is used to guide the others to move towards it. The exploration operator "DE/rand/1″ randomly selects three mutually different individuals to generate a new individual that scans a wider space than the local search, thereby showing a strong global search ability. The hybrid mutation strategy combines the two operators to obtain both their advantages in the proposed algorithm, as shown in Equation (12).

$$\boldsymbol{V}_i = \begin{cases} \boldsymbol{X}_{r1} + F_i \times (\boldsymbol{X}_{r2} - \boldsymbol{X}_{r3}) & \text{if rank}(\boldsymbol{X}_i) \ge \xi \\ \boldsymbol{X}_i + F_i \times (\boldsymbol{X}_{\mathbf{best}} - \boldsymbol{X}_i + \boldsymbol{X}_{r2} - \boldsymbol{X}_{r3}) & \text{otherwise} \end{cases} \tag{12}$$

where $r1$, $r2$, and $r3$ are three random and mutually different individual indices, and $\boldsymbol{X}_{\mathbf{best}}$ is the solution that ranks first after nondominated sorting and crowding distance ranking.

To balance global and local searches, individuals with better performance use the exploitation operator for mutation, whereas individuals with worse performance are assigned to the exploration operator. Because the individuals are sequenced by non-dominated sorting and crowding distance in the initialisation and selection processes, it is possible to recognise which operation should be used for each individual. Coefficient ξ is then defined, as shown in Equation (13), which indicates the boundary between the two individual groups assigned to different mutation operators. If $\boldsymbol{X_i}$ does not belong to the top ξ in the current generation (rank ($\boldsymbol{X_i}$)≥ξ), it means that individual $\boldsymbol{X_i}$ has a worse performance in the current population. An exploration operator was selected for each of these individuals. Otherwise, the individuals are more likely to have better performance, and a local search is more desirable; therefore, the DE/current-best/1 operator is applied. Consequently, the operator used for the mutation operation depends on the performance of $\boldsymbol{X_i}$. Equation (13) assigns more individuals to the exploration operator in the early generations to guarantee population diversity. In the later generations, most individuals are assigned to the exploitation operator because the performance of most individuals should be good after the evolution of previous generations.

$$\xi = \frac{Gen}{MaxGen} \times NI \tag{13}$$

2.4. Convergence condition

The evolutionary process of optimisation can commonly be terminated if one of the following conditions is met: (1) the true Pareto front is acquired, or (2) the algorithm iterates a predefined number of generations. However, because the true Pareto front is unknown for most real-world issues, the convergence condition in this study is to reach the set maximum generation number.

3. Case study

In this section, the efficacy of the proposed MOSHDE for a sustainable highway pavement network maintenance plan is compared with other multi-objective heuristics by applying them to a case study that addresses the maintenance plan of a highway pavement network in Sichuan Province, China.

3.1. General description

The highway network considered in the case study consists of 23.389 km in 15 highway sections. All sections are double-3.75 m-lane pavement, and their lengths and initial PCI values are summarised in Table 1.

Considering the various properties of the maintenance treatments available in the province, several maintenance treatments were defined for the case study, including four preventive treatments (i.e. slurry seal (SS), chip and fog seal (CF), micro-surfacing (MS), and thin overlay (TO)) and three rehabilitation treatments (hot in-place recycling (HIR), resurfacing (RS), and reconstruction (RC)). The mix design of treatments is determined by the technical guidelines applied in the region (Department of Transportation of Sichuan Province, 2014), and the parameters needed to compute the sustainability performance of the maintenance plans are listed in Table 2. The service life and application scope of treatments were determined through a comprehensive analysis of the literature, including academic publications (Huang et al., 2021; Shi, 2019; Torres-Machi et al., 2017; Tran et al., 2022) and, technical guidelines applied in the province (Department of Transportation of Sichuan Province, 2014), and communication with highway managers of the case project. In addition, the effectiveness of different treatments in the optimisation process is computed by the pavement condition deterioration model and treatment service life with the assumption that the treatment cannot only restore the PCI value but can also restore the deterioration rate based on the new PCI value (Lu, 2011; Lu and Tolliver, 2012).

The minimum PCI value was 50. The budget restriction was estimated through the reactive maintenance policy adopted by most highway agencies in China, in which RS is used to maintain pavements with severe deterioration. Such a maintenance plan, namely, the base case, is used to simulate the sustainability performance of the current maintenance policy. The agency budget for maintenance is ¥ 39.451 million.

In this case study, the pavement deterioration model was considered as shown in Equation (14), which Shi (2019) proposed for similar pavements in China. Although the performance model may not strictly reflect the condition development of other pavements, it does not affect the optimisation process, which is the main purpose of this study.

Table 1
Pavement section length and initial PCI of the analysed network.

No.	Length	PCI	No.	Length	PCI	No.	Length	PCI
1	1.728	67.5	6	2.798	84	11	1.647	75.3
2	2.311	64.6	7	1.394	95.6	12	2.895	81.7
3	1.19	74	8	0.517	91.4	13	0.472	95.3
4	2.355	76.4	9	1.304	87.2	14	1.910	91
5	0.915	79.6	10	0.85	79	15	1.103	82.1

Table 2
Unit CE, cost, and service life of considered treatments.

Treatment	CE (kg/m^2)	Cost (10^3 ¥/km)	Service life	Application scope (PCI)
DN	0	0	0	50–100
SS	0.58	29.42	1 year	80–90
CF	1.49	71.25	3 years	75–90
MS	3.15	86.25	4 years	70–90
TO	4.14	131.25	5 years	65–90
HIR	4.87	318.75	5 years	60–90
RS	14.21	487.5	8 years	50–90
RC	24.82	1143.75	12 years	0–90

$$PCI(t) = 100 - \frac{100}{1 + e^{4.631 + 0.339 \times t}} \tag{14}$$

where t is the year after the pavement was finished.

3.2. Mathematical experiment

The four heuristics were coded in MATLAB R2021b and executed on a laptop with 16 GB of RAM and an Intel Core CPU of 2.3 GHz. A preliminary analysis was performed following the execution results of many runs to determine the appropriate parameter values for each algorithm, as shown in Table 3. As suggested by Piotrowski, the appropriate population size of DE for real-world optimisation problems with more than 40 variables can be up to 10D (D denotes the number of variables) (Piotrowski, 2017); the population were initialised as 4500 different individuals. The maximal generation number was set as 20000, determined based on a preliminary analysis to balance the algorithm performance and execution time.

Because of the stochastic property of heuristics, the experimental results should be compared using statistical analysis methods. The most direct method would be to run each heuristic a specific number of times independently and conduct a statistical analysis of the experimental results. However, because of the complexity of the problem, each execution can be computationally expensive. Given this, by analysing the variability of the results of several preliminary runs, we decided that each algorithm would be executed ten times.

3.3. Assessment of heuristics

To understand the performance of the proposed heuristic, the resulting approximate Pareto fronts of different multi-objective heuristics should be compared. However, it is difficult to compare the approximate Pareto fronts straightforwardly, as the objective functions are conflicting and the numbers of solutions in the approximate Pareto fronts are different. One popular evaluation metric is the hypervolume (HV), which can map an approximate Pareto Front to a single value to compare different heuristics (Zitzler et al., 2003). Briefly, HV indicates the volume of the dominant area of the obtained approximate Pareto front in the objective space. Therefore, a heuristic that can produce a Pareto front approximation with a greater HV tends to be better for the non-dominance relationship (Crespo-Cano et al., 2019).

Meanwhile, the diversity of solutions is also considered as a metric to compare these heuristics, as an approximate Pareto front that includes more diverse solutions could enable decision makers to choose a maintenance plan among multiple balanced options that better serve their interests and thus is more desirable. Here, a metric, entropy, is used to evaluate the diversity of approximate Pareto solutions (Pires et al., 2013). The entropy measures the uncertainty of a variable that estimates the information content of a solution set. An approximate Pareto set with a larger entropy tends to be more diverse because more information should be contained in it.

Other assessment metrics, such as inverted generational distance (Monsef et al., 2019), are not applicable in this study, as the true Pareto front is unknown.

Table 3
Settings of compared heuristics.

Algorithms	NSGA-II	MODE	MOPSO
Parameters	Crossover rate = 0.9	Mutation factor = 0.2	Inertia weight = 0.1
	Mutation rate = 1/15	Crossover rate = 0.1	C1 = 0.5
			C2 = 0.5
			Mutation rate = 1/15

4. Experimental results and discussion

4.1. Comparative analysis of different heuristics

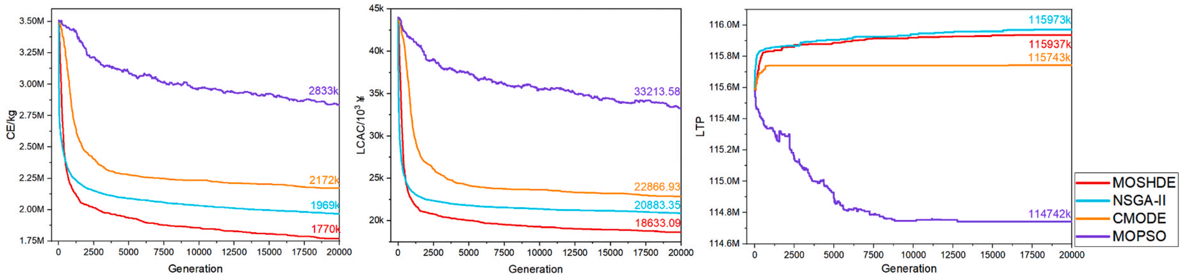
Fig. 4 shows the average best objective function values for all runs over generations, and Table 4 shows the final best objective function values in the Pareto sets obtained by each tested heuristic in different runs, where the best values in each run are highlighted in bold. Overall, all tested heuristics can obtain several feasible solutions, of which the LCACs are less than ¥ 39.451 million. The MOSHDE has the fastest convergence speed in terms of CE and LCAC. Although it converges slower with LTP than NSGA-II, the difference is slim, and thus, the convergence speed can be regarded at the same level. Moreover, MOSHDE captured the best objective function values of CE and LCAC in all executions, and in terms of LTP, outperformed the others in most runs.

NSGA-II showed a premature convergence feature, which is a common problem for GAs (Pandey et al., 2014). NSGA-II was the most efficient in the early stage of the evolution (the first 460 generations), but its efficiency rapidly decreased afterwards, and the objective function values converged to worse values than those of the MOSHDE.

MOPSO was the worst in terms of efficiency, and extreme values were obtained. MOPSO updates the positions of individuals based on personal and global guides, which cannot guarantee that the descendant is better than its parent, as the objective function values of descendants in some generations were worse than those of previous generations (especially in LTP). Based on the experimental results of this study, it can be concluded that the search mechanism of MOPSO is less efficient than that of the others, in which individuals are ranked and selected based on non-dominated sorting and crowding distance ranking.

MOSHDE was better than CMODE for all three objectives and convergence rates. Three reasons can explain this difference. First, in the CMODE, only one mutation operator is used; thus, only one of the exploitation or exploration abilities can be implemented. The MOSHDE processes exploration and exploitation together; thus, the advantages of both exploration and exploitation can be achieved. Second, the step size of the iterations in the evolution is defined by the control parameters. For individuals with better performance, a smaller step size is more desirable for exploitation and vice versa. Therefore, the appropriate control parameters for different individuals at different evolutionary stages should differ according to their performance. In CMODE, the control parameter remains the same all the time, which means that the iteration step size is the same for all generations. By comparison, the self-adaptive parameter control strategy embedded in the MOSHDE can automatically adjust the step size for each individual in different evolution stages, thus improving the efficiency and robustness of the algorithm.

Moreover, in mutation and crossover operations, many fragments of the parent vector are changed to obtain a descendant. Let one of the changed fragments in the descendant be denoted as $u_{y,n}^{i}$. The PCI value in the corresponding position (y,n) of the descendant, denoted as $PCI_{u_{y,n}^{i}}$, is determined by its former fragments of the same pavement section (i.e.,



(a) CE objective function value　(b) LCAC objective function value　(c) LTP objective function value

Fig. 4. The average value of the best objective function values over 20000 generations.

Table 4
Final best objective function values obtained by tested heuristics in each execution.

Execution No.	1	2	3	4	5	6	7	8	9	10
CE ($\times$ 10^3 kg)										
MOSHDE	**1750**	**1753**	**1898**	**1758**	**1683**	**1810**	**1879**	**1770**	**1767**	**1628**
NSGA-II	2019	1889	2028	2005	1970	1974	2156	1937	1833	1876
CMODE	2003	2357	2275	2001	2165	2081	2157	2079	2306	2296
MOPSO	2741	2916	2796	2948	2839	3028	2674	2615	2783	2995
LCAC ($\times$ 10^3 ¥)										
MOSHDE	**18671**	**17314**	**20366**	**17916**	**17552**	**19399**	**20128**	**19005**	**18393**	**17586**
NSGA-II	21149	20339	21974	21522	20167	20656	23123	21439	18673	19791
CMODE	21047	25912	23745	21086	22024	21332	22700	21807	25104	23912
MOPSO	33702	33358	32259	34047	32130	36466	30888	31281	33676	34329
LTP ($\times$ 10^3)										
MOSHDE	**115390**	115212	**115151**	**115404**	115050	**115095**	**115255**	115058	**115504**	**115395**
NSGA-II	115365	**115320**	115138	115087	**115396**	114881	114983	**115246**	115337	115251
CMODE	114447	114270	114370	115018	114307	113341	114034	114949	114045	114349
MOPSO	111907	111542	111047	109794	111725	110506	111629	111437	112113	110261

$u^i_{1,n}$, ⋯, $u^i_{y-1,n}$). Therefore, there is a probability that $PCI_{u^i_{y,n}}$ is outside the application scope of $u^i_{y,n}$, which would lead to failed evolution. In CMODE, if one generation of evolution fails, the descendant will be replaced by the parent vector; thus, the same probability of failure will remain in the next generation, as the control parameters are always the same. Compared with CMODE, in MOSHDE, because the parent vector and descendant have the same performance if the evolution fails, a new pair of control parameters is assigned to the individual to avoid further failure in later generations, thus enhancing the probability of successful evolution.

Figs. 5 and 6 show the distribution of the HV and Entropy values of the obtained Pareto Front approximation in the last generation of the ten

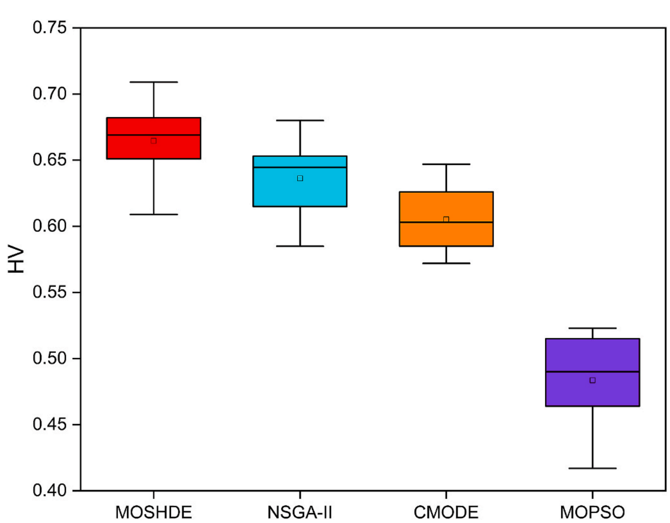


Fig. 5. Distribution of HV values for ten independent executions of all heuristics.

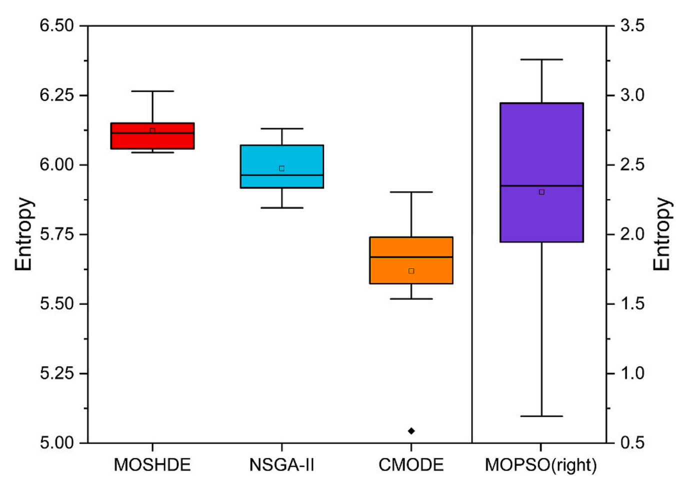


Fig. 6. Distribution of Entropy values for ten independent executions of all heuristics.

experimental executions. The mean and median values of the two metrics of the proposed MOSHDE are the greatest. When one front dominates another one, the HV of the former shall be greater than it of the latter. To better analyse the HV results of independent executions, the Mann-Whitney *U* test (Bergmann et al., 2000) was conducted pairwise to decide whether the results of MOSHDE were significantly better than others. The test's null hypothesis was defined as the HV data of MOSHDE not being significantly different from those of the other methods compared, i.e., the HV data of MOSHDE being outperformed. The significance level was set as 0.05. The pairwise results are listed in Table 5, and all p-values of the tests are less than 0.05. Thus, the null hypotheses were rejected, meaning the results of MOSHDE were significantly better than the others. The same test was also conducted to compare the

Table 5
P-values of the Mann-Whitney *U* tests.

	MOSHDE versus NSGA-II	MOSHDE versus CMODE	MOSHDE versus MOPSO
HV	0.0077	0.0002	0.0001
Entropy	0.0056	0.0001	0.0001

entropy metric, and the result was similar to the HV test, which shows that the approximate Pareto-optimal solutions obtained by MOSHDE are more diverse, thus providing more options to decision-makers to meet their specific needs.

To enhance our understanding of the performance of these heuristics, we illustrate the Pareto-front approximation with the best entropy values of the tested heuristics in Fig. 7. All data were represented by drawing a comparison in pairs for each sustainability objective. It is clear that most of the solutions obtained by the proposed MOSHDE dominate most of the others and are evenly distributed in a broader range in the objective function space than the others, which is consistent with the HV and entropy comparison. In addition, we found it interesting that CE and LCAC are positively correlated on the Pareto front, meaning it is possible to optimise the performance in both objectives simultaneously.

4.2. Practical implications

We believe that the comparisons between the heuristics performed in this study can prove the superiority of the proposed algorithm. Therefore, the results obtained by MOSHDE are further analysed in this section to obtain practical recommendations. In fact, all execution results show the same trend; therefore, we select the solution set with the best entropy value for this analysis. To better understand the obtained solutions in MOO, three solutions were selected as optimal solutions for further analysis: the solution corresponding to the lowest CE (denoted as CEmin), the solution corresponding to the lowest LCAC (denoted as LCACmin), and the solution corresponding to the greatest LTP (denoted as LTPmax).

Fig. 8 shows the application rates of the applied treatments in the optimal solutions, of which the total execution numbers of maintenance activities are 108, 104 and 89, respectively. The application rates of preventive treatments are 96% in CEmin and LCACmin and 65% in LTPmax, indicating that optimal solutions follow a proactive policy. At this point, it should be noted that preventive treatments are less intensive and can only treat pavement defects to a low extent, which is why they are applicable only at high PCI levels. This result indicates that maintaining the pavement in good condition in a proactive way can improve the sustainability performance of the pavement, which is aligned with the conclusion derived from (Torres-Machi et al., 2017). Among the four preservations, it can be concluded that CF has the best performance regarding environment and economy as it has the greatest application rate in CEmin and LCACmin. Similarly, TO is the best preventive treatment for maintaining pavement conditions. As for

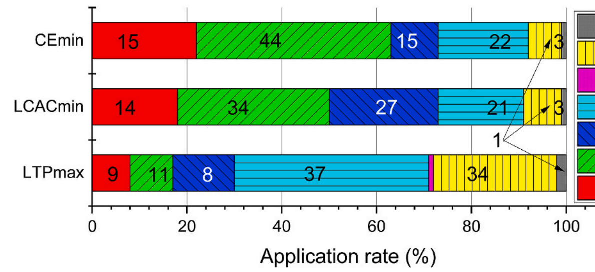


Fig. 8. Application rate of maintenance treatments in optimal solutions.

rehabilitation treatment, RS has good performance in terms of LTP due to its application rate in LTPmax, but other rehabilitations are rarely used in all optimal solutions. Therefore, they are not sustainable. Such conclusions can be used to guide practitioners in selecting treatments to maintain their pavements according to their specific preferences.

Table 6 lists the objective function values for the three optimal solutions. The base case is also listed for comparison. The objective function values of CEmin and LCACmin are very close, which echoes the conclusion obtained from the positive correlation between CE and LCAC on the Pareto front (Fig. 7 (a)). By adopting a proactive maintenance policy, it is possible to reduce the environmental impacts of pavements while saving the budget for highway agencies. Compared with the base case, except that LTPmax has a slightly higher value than the base case in CE, all the objective function values of the optimal solutions are better than those of the base case, with reductions of up to 57% in CE and 55% in LCAC and increases of up to 202% in LTP, indicating that the proposed algorithm is capable of finding a set of maintenance plans that are far more sustainable than those adopted in current practice.

5. Conclusion

This study proposed a new variant of the MODE algorithm, named MOSHDE, which incorporates self-adaptive control parameters and hybrid mutation operators. Subsequently, the proposed MOSHDE was applied to formulate a sustainable pavement maintenance plan for an actual highway network in China and its performance was compared with those of NSGA-II, CMODE, and MOPSO. The Mann-Whitney *U* test of HV and entropy metrics were used to evaluate the quality and diversity of the approximate Pareto-optimal set obtained. The experimental results indicate that MOSHDE converges faster, provides better values of the three sustainability metrics considered, and delivers an

Table 6
Objective function values of optimal solutions and the base case.

	CEmin	LCACmin	LTPmax	Base case
CE (10^3 kg)	1628	1677	3822	3787
LCAC(10^3 ¥)	17931	17586	39399	39451
LTP (10^3)	95499	95223	115395	38087

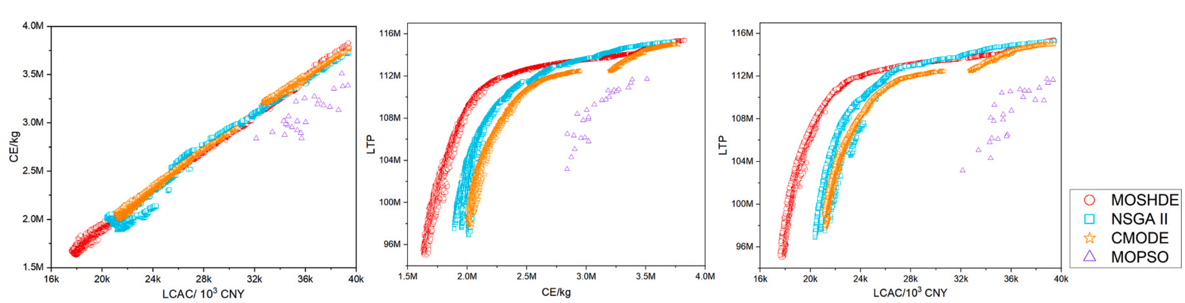


Fig. 7. Pareto-optimal approximation of different heuristics facing each pair of objectives.

approximate Pareto front with significantly higher quality and diversity (as per the HV and entropy metrics) than the other three heuristic algorithms evaluated.

We believe that the proposed MOSHDE was able to outperform other heuristics in the experiment because it addressed some issues and limitations observed in the existing literature. First, many heuristics perform only exploitation or exploration searches during the optimisation process. However, exploitation and exploration have unique advantages that cannot be replaced by each other. Instead, the hybrid mutation strategy in MOSHDE assigns individuals with better performance to exploitation and those with worse performance to exploration, thus maintaining a balance between global and local searches.

Second, many heuristics heavily rely on the appropriate tuning of control parameters, which usually need to be determined based on time-consuming empirical tests and practical experience, although this cannot guarantee an adequate performance of the set parameters. The self-adaptive parameter control strategy embedded in the MOSHDE framework can avoid this time-consuming process of selecting the appropriate control parameters, enhancing the robustness and applicability of MODE. In addition, as mentioned in the discussion section, this self-adaptive mechanism can significantly improve the efficiency of the algorithm by reducing the probability of failed evolution due to the PCI value falling outside the scope of application of the treatment in the optimisation process.

Furthermore, this study not only developed a new heuristic to solve a PNMOP, but also compared several state-of-the-art heuristics using a case study and various performance metrics. The results can provide a reference for future researchers when selecting or developing algorithms to optimise pavement maintenance plans.

Finally, three optimal solutions with the best objective function values in the Pareto-optimal set obtained via the proposed method were further analysed as suggested proactive maintenance policies. Compared with the reactive policy that is currently adopted in China, the optimal solutions have better objective function values, indicating that the proposed approach can help highway operators maintain their pavement networks in a more cost-effective way, limit the environmental impacts of maintenance activities, achieve better pavement performance over the project life cycle, and provide audiences fair and advantageous socio-demographic benefits by delivering more serviceable pavement networks to highway users.

The algorithm presented in this study has demonstrated that it can help practitioners in developing sustainable highway infrastructure. In the future, to conduct a more comprehensive analysis, we will apply the proposed model to formulate the maintenance plan of more complex highway pavement networks, considering more sustainability metrics (e.g. NO_x and SO_x emissions, and road user cost) and more life cycle phases (e.g. work zone management and use phase) among the system boundaries.

CRediT authorship contribution statement

Junda Li: Conceptualization, Methodology, Software, Writing – original draft. **Michael Pitt:** Conceptualization, Methodology, Supervision, Project administration. **Ling Ma:** Conceptualization, Methodology, Supervision, Project administration, Writing – review & editing. **Jing Jia:** Resources. **Feng Jiang:** Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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