# Game theory-based bilevel multi-objective model for multi-player pavement maintenance management

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**Abstract**

Maintenance of pavements is widely thought to be critical for promoting their sustainability, playing a pivotal role in sustainable and resilient transportation infrastructure for growth in economic development and improvements in social inclusion. Existing research mainly focuses on optimizing the maintenance strategies from one-player but ignores the inherent conflicts and complex interactions among multi-player decision-makers. To address these issues, this research examines the problem of pavement maintenance involving the highway agency and the maintenance service providers under the uncertainty of pavement conditions with the aim of optimizing maintenance strategies. A novel bilevel mathematical model with multiple objectives is proposed to handle the inherent conflicts and complex interactions among decision-makers based on the Stackelberg game and Nash game for obtaining the Stackelberg-Nash equilibrium solution, in which the highway agency, as the upper-level leader, determines the maintenance tasks, while the service providers, as the lower-level followers, provide the corresponding maintenance activities. To address the complex model, a bilevel particle swarm optimization (BLPSO) algorithm is developed for pavement maintenance. Finally, a practical case is used to demonstrate the practicality and efficiency of the proposed model. The results and the further comparison analysis show that the proposed mathematical model can provide a feasible and effective pavement maintenance strategies for multi-player decision-makers in the real-world application.

**Keywords:** Pavement maintenance; Bilevel particle swarm optimization; Stackelberg-Nash game, Leader-follower strategy.

## 1. Introduction

The demand for pavement maintenance of the existing transportation infrastructure has grown rapidly owing to the large-scale transportation infrastructure expansion in China in the past 20 years [1]. Pavement maintenance is considered to be a pivotal backbone of sustainable and resilient transportation infrastructure and receives considerable attention from both academia and industry for growth in economic development and improvements in social inclusion [2-5]. Accordingly, pavement maintenance is widely recognized as an effective way of maintaining or improving the pavement performance to ensure the safety and extend the service life of the pavement [6-9]. Statistically, the maintenance expense of the transportation infrastructure accounts for a large amount, may double the construction cost [10], and thereby, directly affecting the total costs as well as playing an important role in the lifecycle of the transportation infrastructure.

Generally, a good road management is of crucial importance for adequate pavement maintenance, because it has the potential to provide multi-player decision-makers, including highway agency and service providers, with the required guidance to achieve both high performance and cost-effectiveness of the maintenance [11]. The highway agency is responsible for selecting service providers, task assignment, and how to pay the service providers, while the service providers are allocated the responsibilities of performing required services for the highway agency. However, most previous studies quite often adopted a centralized perspective that the highway agency is in a central position to control and rigidly implement all strategic and operational decisions, but sometimes inconsistently with an actual situation. This issue is still largely unexplored. In practice, all decision-makers possess a level of liberty in choosing their strategies in their benefits to maximize profits during the job delivery. Thus, the maintenance process is commonly decentralized while conflicts and interactions occur frequently. In the interactive maintenance process, the highway agency is often concerned about a maintenance strategy with a limited budget but the highest possible service quality for a good reputation, while service providers focus mainly on their profit. Owing to incompatible or opposite pursuits, in many cases conflicts are inevitable. If not handled well, their impact will damage maintenance operations with undesirable consequences, such as economic losses or even injuries. Thus, to reach a satisfactory solution for all stakeholders, the pavement maintenance management problem should target at an optimal strategy for maintenance contents that consider conflicts and interactions among the highway agency and service providers.

To address the multiple-party pavement maintenance management problem, it is necessary to analyze the roles of all players, the highway agency and service providers, involved in the pavement maintenance process and integrate their interactions. The highway agency has the natural privilege to develop firstly its maintenance strategies. For service providers, profits are their goal in determining their strategies while simultaneously considering the competition among them. To handle the inherent conflicts and analyze complex interactions, and achieve equilibrium among all decision-makers, this research proposes a novel bilevel mathematical model based on the game theory, simultaneously considering requirements and restrictions in practice.

The organization of this research is as follows. After a brief review of the relevant literature, the research problem is formulated. Next, the bilevel mathematical model is developed, including the Stackelberg-Nash game model, and correspondingly bilevel particle swarm optimization method to obtain the Stackelberg-Nash equilibrium solution. The proposed methodology is verified by a numerical example and compared with the traditional single-player method to highlight its advantages. Finally, a comprehensive conclusion is drawn.

## 2. Literature Review

Pavement maintenance has received extensive attention worldwide. An appropriate pavement maintenance strategy is of crucial importance for sufficient pavement maintenance to promote pavement sustainability [12]. For obtaining pavement maintenance strategies, researchers have made unremitting efforts, mainly focusing on project-level and network-level pavements [13]. In the study by Yu et al. [14, 15], pavement maintenance models are proposed to optimize the plans considering the pavement performance, environmental impacts, and cost. Itoya et al. [16] explored a carbon tool by a lifecycle assessment approach to determine pavement maintenance strategies. A systematic decision-making process is suggested by Yoon et al. [17] by considering pavement conditions. Yeon et al. [18] developed a new repair technology for pavement maintenance by conducting environmental impact assessments via the economic input-output life cycle assessment. In addition, extensive research has been carried on exploring the network-level pavement maintenance. Kuhn [19] presented a method using approximate dynamic programming based on multidimensional condition data for pavement network maintenance optimization. Mathew and Isaac [20] developed an optimization model for optimizing pavement maintenance strategies satisfying two objectives: maximization of pavement performance and minimization of maintenance cost using the genetic algorithm. Chen et al. [21] established a model to address a bi-objective optimization problem of maximizing the benefit and minimizing the cost under annual budget and condition requirements for pavement maintenance decision-making. France-Mensah and O'Brien [4] improved a model for pavement maintenance optimization integrating road conditions, road user costs, and greenhouse gas emissions. Yao et al. [22] applied deep reinforcement learning to obtain the better maintenance strategies by maximizing the long-term cost-effectiveness in maintenance decision-making considering 42 features related to pavement structures and materials, maintenance records, traffic loads, pavement conditions, and so forth. Undeniably, most of the proposed methods achieve good performance for optimizing pavement maintenance strategies in specific scenarios whether at the project level or network level. However, in the existing research, maintenance strategies are mainly formulated from a one-player decision maker's perspective by simultaneously pursuing the maximization of individual profits. As stated above, pavement maintenance involves multiple parties to decide on the delivery of maintenance tasks. The need of taking multi-player decision-makers as a whole to discuss and analyze their conflicts and interactions for pavement maintenance has motivated us in this work.

Game theory mainly studies conflicts and interactions among multi-player decision-makers to determine optimal strategies considering the involved process at both internal and external levels, or the same and different levels [23]. The game theory research has attracted much attention in many fields, such as applications in bargaining [24], bidding [25], sequential ordering [26], safety management [27], climate change adaptation [28], supply chain [29], and online optimal control of energy systems [30]. In the study by Asgari et al. [31], a cooperative game theory is proposed to address the joint resource management problem in construction by analyzing the interactions at the internal level between subcontractors. Fathi Aghdam and Liao [32] applied a Stackelberg game model for joint decision making in preventive replacement scheduling and competition in service parts procurement via dealing with the interactions at the external level between one operator as leader and another as follower. Zhou et al. [33] developed the Stackelberg game and Nash game on the financing problem between manufacturer guarantor and third-party logistics guarantor considering the interactions at both internal and external levels among a manufacturer, a logistics third party, a capital constrained retailer, and a bank. The game theory approach has achieved fruitful results but is rarely applied in pavement maintenance and remains an opportunity to explore for satisfactorily handling the conflicts as well as interactions among multi-player decision-makers.

From the motivation and the literature survey, this research proposes a novel bilevel mathematical model with multiple objectives based on the Stackelberg and Nash game model, where the highway agency as the upper-level leader determines the maintenance tasks, and the service providers as the lower-level followers provide the corresponding maintenance activities, to resolve the conflicts and accommodate interactions among multi-player decision-makers in pavement maintenance. Afterward, it is granted for finding a solution for the game equilibrium.

As can be expected, the novel bilevel mathematical model mainly based on a number of assumptions and formulation derivations remains a very complex and difficult task to find optimal solutions, which may hinder its wide application. In terms of feasibility for such a solution to the novel bilevel mathematical model, many attempts have been made and heuristic solution methods are frequently opted. Xu and Zhao [34] developed an interactive bilevel PSO algorithm for the complex bilevel model of the supplier selection and dynamic inventory. Eltoukhy et al. [35] proposed an ant colony optimization based-algorithm to determine a bilevel optimal solution for the problem of flight delay-based operational aircraft routing and staffing. Liu et al. [36] and Chang et al. [37] applied bilevel nested parallel solution algorithms with the genetic algorithm for the bilevel model in product line design and component maintenance, respectively. Thus, the heuristic solution methods are feasible methods to solve bilevel model for obtaining the optimal solution. These noticeable applications of heuristic solution methods motivate the authors to examine their performance in the pavement maintenance problem. To this end, a bilevel mathematical model with multiple objectives based on the Stackelberg-Nash game is proposed in this paper to resolve the conflicts and interactions among the highway agency and service providers to determine the optimal strategies for the pavement maintenance problem via a bilevel PSO (BLPSO) algorithm.

## 3. Problem description

Here, the multi-player decision-makers include a highway agency and several service providers. They are integrated to provide service strategies and activities to ensure pavement performance and promote pavement sustainability. In the long term, the highway agency, as the leader, has a significant influence in the decision-making, the service provider as the follower is expected to make a rational response to the agency's decisions. Once there is pavement damage affecting normal traffic, the highway agency first develops maintenance strategies considering total costs, while each service provider, obtaining the maintenance information from the highway agency, will determine its own output measures to be provided simultaneously with feedback to the highway agency in each maintenance job. Since different decision-makers have different objectives, the highway agency's optimal plan may not meet the service providers' willingness, resulting in inevitable conflicts. For example, the highway agency expects lower maintenance costs whereas the service providers may seek more profits counting on as many service items as possible, which may lead to high maintenance costs. To address the critical problem, a feasible decision method developed from the game theory is expected to resolve the conflicts and interactions among the highway agency and service providers.

From the vertical perspective of leader-follower interactions, the highway agency has on one hand the decision-making advantage to possibly bring in profits. Therefore, the highway agency needs to comprehensively consider the profits obtained when making decisions to appropriately allocate certain benefits and funds to prevent service providers from refusing to participate in pavement maintenance. To address the issues among the highway agency and service providers, a Stackelberg game is used to model involved interactions. On the other hand, from the horizontal perspective of decision-makers' interactions, owing to the limited maintenance tasks assigned by the highway agency and service capability, the service provider will make an independent decision to accomplish the assignment, trying to strive for as many tasks as possible to obtain more profits. However, a long-term competition among service providers may easily produce negative emotions further leading to adverse impacts on maintenance operations, complicating the scenario. To handle conflicts and achieve a win-win situation among service providers, the Nash game is applied to model their conflicts and interactions.

In summary, to model potential conflicts and interactions among all decision-makers, a bilevel mathematical model with multiple objectives based on the Stackelberg game and Nash game is proposed, which is to deal with the conflicts and interactions among the highway agency and service providers.

## 4. Methodology

### 4.1 Game theory framework

Game theory, as an important branch of mathematics, is the study on conflicts and interactions among rational and intelligent decision-makers [28, 38, 39]. The decision-maker of a game can make decisions to pursue their individual objectives by simultaneously considering the possible objectives, behaviors, and countermeasures of other decision-makers to achieve a win-win situation. For this, the Stackelberg game and Nash game are frequently used, which is aligned well with the problem involved in the current research. The Stackelberg game is a first move advantage strategy model to resolve the asymmetric competition among the leading decision-maker and the following decision-makers, respectively highway agency and service providers in our case, subject to the order of action: the leader first makes a decision then by the followers decide on their own to respond to the leader's decision [40]. Therefore, the Stackelberg game could as an appropriate approach to model the potential conflicts and interactions among the highway agency and the service providers. The Stackelberg game can be expressed as:

$$\mathrm{G}_S = \left((N^l, N^f), (S^l, S^f), (U^l, U^f)\right), \tag{1}$$

where $(N^l, N^f)$ is the decision-makers' set, $N^l$ represents leading decision-maker (the highway agency), and the $N^f$ represents following decision-makers defined as the set $N^f = \left(N_1^f, N_2^f, \cdots, N_n^f\right)$, with $N_i^f$ being the $i$-th service provider. The pair $(S^l, S^f)$ stands for the decision-makers' strategy set, where $S^l$ represents leading decision-makers' strategy set defined as $S^l = \left(s_1^l, s_2^l, \cdots, s_m^l\right)$ with $s_i^l$ being the *i*-th decision strategy made by the highway agency. The strategy set of *n* service providers is $S^f = \left(s_1^f, s_2^f, \cdots, s_n^f\right)$, where $s_i^f = \left(s_{i1}^f, s_{i2}^f, \cdots, s_{im_i}^f\right)$ represents all $m_i$ decision strategies made by the *i*-th service provider. The set $(U^l, U^f)$ represents the decision-makers' profits.

The Stackelberg equilibrium is defined as $s_s^* = (s^{l*}, S^{f*})$, which satisfies

$$\mathrm{U}^f(s^l, s^l(S^{f*})) \geq \mathrm{U}^f(s^l, s^l(S^f)) \tag{2}$$

$$\mathrm{U}^l(s^{l*}, S^{f*}(s^{l*})) \geq \mathrm{U}^l(s^l, S^{f*}(s^l)), \tag{3}$$

where $s^{l*}$ and $S^{f*}$ represent the optimal strategies of the leader and the followers, respectively. The relations $S^f(s^l)$ and $s^l(S^f)$ represent the following decision-makers' strategy set $S^f$ with respect to the leader's strategy $s^l$ and vice versa. Then, $s_s^* = (s^{l*}, S^{f*})$ can be obtained

$$S_s^* = argmax\mathrm{U}^f = argmax\mathrm{U}^l \text{ subject to } s_s \in S_s. \tag{4}$$

The Nash game is commonly applied to the situation of all decision-makers in the symmetric competition [41]. In the Nash equilibrium situation, each decision-maker cannot obtain any more profits as long as others do not change their strategies. The Nash equilibrium provides an approach to predict optimal results for all symmetric decision-makers, which is well suited to deal with the conflicts and interactions among symmetric decision-makers to be applied in this research. The Nash game can be expressed as:

$$\mathrm{G}_N = (N^f,\ S^f,\ U^f). \tag{5}$$

The Nash equilibrium can be defined as $s^{f*} = \left(s_1^{f*}, s_2^{f*}, \cdots, s_n^{f*}\right)$ when

$$\forall\ \mathrm{s}_{ij}^f \in S_i^f,\ \mathrm{U_i^f}\left(s_i^{f*}, s_{-i}^{f*}\right) \geq \mathrm{U_i^f}\left(s_{ij}^f, s_{-i}^{f*}\right),\ i = (1,2,\cdots.\mathrm{n}), j = (1,2,\cdots,m_i),$$

where $s_{-i}^{f*} = \left(s_1^{f*}, \cdots, s_{i-1}^{f*}, s_{i+1}^{f*}, \cdots, s_n^{f*}\right)$ is the optimal strategy set of other decision makers with respect to $s_i^{f*}$. The Nash equilibrium strategy made by the *i*-th service provider $s_i^{f*}$can be obtained as

$$s_i^{f*} = argmax\ \mathrm{U_i^f}\left(s_1^f, \cdots, s_{i-1}^f, s_i^{f*}, s_{i+1}^f, \cdots, s_n^f\right),\ j = (1,2,\cdots,m_i). \tag{6}$$

According to the above game models, the Stackelberg-Nash game is now expressed as follows [37]:

$$\mathrm{G} = \left((N^l, N^f), (S^l, S^f), (U^l, U^f)\right). \tag{7}$$

The Stackelberg-Nash equilibrium $(s^{l*}, s_1^{f*}, s_2^{f*}, \cdots, s_n^{f*})$ can be obtained subject to:

$$\forall s_{ij}^{f} \in S_{i}^{f},\ \mathrm{U}_{\mathrm{i}}^{\mathrm{f}}(\mathrm{s}_{\mathrm{i}}^{\mathrm{l}},\mathrm{s}_{\mathrm{i}}^{\mathrm{f*}},\mathrm{s}_{\mathrm{-i}}^{\mathrm{f*}}) \geq \mathrm{U}_{\mathrm{i}}^{\mathrm{f}}(\mathrm{s}_{\mathrm{i}}^{\mathrm{l}},\mathrm{s}_{\mathrm{ij}}^{\mathrm{f}},\mathrm{s}_{\mathrm{-i}}^{\mathrm{f*}}),\ \mathrm{i} = (1,2,\cdots,\mathrm{n}), \mathrm{j} = (1,2,\cdots,m_i) \tag{8}$$

$$U_{\Sigma}^{f}(s^{l*}, s^{f*}(s^{l*})) \geq U_{\Sigma}^{f}(s^{l}, s^{f*}(s^{l})), \tag{9}$$

where $U_{\Sigma}^{f}(s^{l}, s^{f*}(s^{l}))$ represents the sum of all decision-makers' profits. Note that inequality (9) indicates the optimistic expectation of the leader for attracting more following decision-makers. The framework of the Stackelberg-Nash game is shown in Fig. 1.

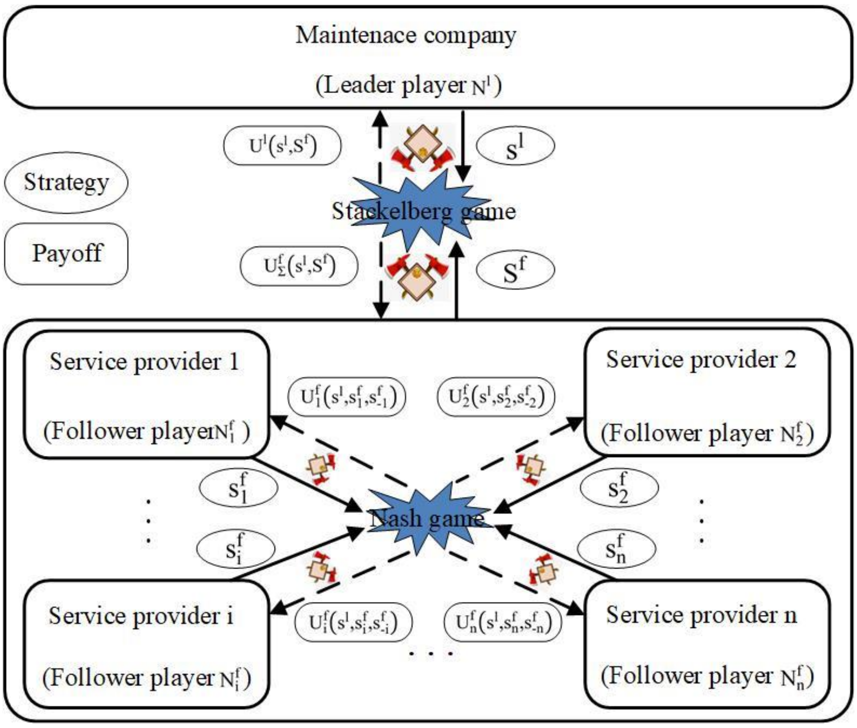



**Fig. 1.** Illustration of the Stackelberg-Nash game.

## 4.2 The upper-level (highway agency) multi-objective optimization model

The highway agency as the leading decision-maker not only pursues the profits, but also concerns the maintenance quality of the road pavement for users, as well as the need to reduce operational costs affected by pavement conditions, as well as corresponding costs including maintenance cost given toll income. In addition, a part of the highway agency's disposable income should be included from the subsidy from the government. Thus, the highway agency budget covers government subsidy, maintenance cost, and toll income. In summary, the multi-objective optimization model for the highway agency is as follows:

$$\mathrm{U}^{l}(m^{t}) = F(\min C, \min UPDs) = \sum_{t=1}^{T}(TI^{t} - SA^{t} - C^{t}), \tag{10}$$

where $C$ and $UPDs$ represent the total maintenance costs and user's pavement dissatisfaction, respectively, $TI^t$ and $SA^t$ are the toll income and government subsidy in year *t*, respectively, and *T* is the maintenance horizon.

4.2.1 Maintenance cost

The maintenance cost, calculated by the maintenance mileage and measures across the five pavement states from excellent ($s_1$), good ($s_2$), fair ($s_3$), poor ($s_4$) to very poor ($s_5$), can be expressed as follows:

$$C = \sum_{t=1}^{T} C^t = \sum_{t=1}^{T}\sum_{i=1}^{n} C_{N_i^f}^t = \sum_{t=1}^{T}\sum_{i=1}^{n}\sum_{j=1}^{5}(MC_{s_jN_i^f}^t \times M_{s_jN_i^f}^t) \quad (11)$$

subject to:

$$0 \le \sum_{j=1}^{5} M_{s_jN_i^f}^t \le M_{N_i^f}^{lt} \quad (12)$$

$$\sum_{i=1}^{n} M_{N_i^f}^{lt} \le TM \quad (13)$$

$$MC^t = MC^{pini} \times (1 + r_c)^{t-5*(p-1)}, \quad (14)$$

where $C_{N_i^f}^t$ represents the maintenance cost of the service provider $N_i^f$, $MC_{s_jN_i^f}^t$ is the unit maintenance cost of service provider $N_i^f$ for pavement state $s_j$, $M_{s_jN_i^f}^t$ is the maintenance mileage of service provider $N_i^f$ for pavement state $s_j$, $M_{N_i^f}^{lt}$ represents the maintenance mileage required by the highway agency for service provider $N_i^f$, $TM$ represents the total maintenance mileage, $MC^{pini}$ is the initial maintenance unit cost in period *p*, and *r* is the discount rate, in which the superscript *t* means in year *t*.

The total maintenance cost (11) is incurred from all service providers participating in the pavement maintenance. For the constraints, (12) implies that the total maintenance mileage performed by service provider $N_i^f$ is naturally smaller than the mileage assigned by the highway agency for service provider $N_i^f$, (13) indicates that the total maintenance mileage of all service providers is limited by the total maintenance mileage required, and (14) expresses the time value of unit maintenance cost at different periods.

4.2.2 Toll income incurred from users' travel willingness

The toll income varies according to the number of vehicles passing by in relation to the user's travel willingness, which may be affected by the users' pavement dissatisfaction on the road pavement conditions [10]. Indeed, there exists a link between the users' pavement dissatisfaction and toll incomes since the traveled road may be optional but not the user's only choice. The toll income can be defined as follows:

$$TI^t = \sum_{j=1}^{q} (UTw^t \times V^t \times TR \times TM) \tag{15}$$

subject to:

$$\mathrm{UPDs}^t = \begin{cases} 100 & PCI < C_1 \\ \frac{C_2 - PCI}{C_2 - C_1} \times 100 & C_1 \le PCI \le C_2 \end{cases} \tag{16}$$

$$UTw^t = \mathrm{UPDs}^t \times \frac{UTw_{min} - 1}{100} + 1 \tag{17}$$

$$V^t = V^{ini} + r_v * t \tag{18}$$

$$0 \le V^t \le V_{max}\ , \tag{19}$$

where $UTw^t$ is the users' travel willingness, $V^t$ stands for equivalent traffic volume in year *t*; $TR$ represents the toll rate, $\mathrm{UPDs}^t$ represents the users' pavement dissatisfaction on the road pavement conditions with $C_1$ and $C_2$ being the two thresholds for it, $UTw_{min}$ is the lowest users' travel willingness reflecting that there will always be vehicles passing by regardless of the road pavement conditions, *PCI* stands for the pavement condition index representing the pavement performance, $V^{ini}$ is the initial equivalent traffic volume, $r_v$ is the annual rate of increased equivalent traffic volume, and $V_{max}$ is the maximum traffic volume considering the road capacity.

It can be seen that the toll income (15) depends on the users' travel willingness, the number of vehicles passing, toll rate, and the total maintenance mileage. Since the toll rate and total mileage do not change significantly during the maintenance horizon, thus, the users' travel willingness, and the number of vehicles passing by becoming the main factors affecting the toll income. The constraints in Eqs. (16) and (17) guarantee that the users' willingness is indirectly but significantly affected by pavement performance. If the road pavement conditions are good, users' pavement dissatisfaction is low, the users' travel willingness to drive increases, which could result in many passing vehicles. If the road pavement condition is not good, users' pavement dissatisfaction is high, the users' travel willingness to drive is poor, and other roads may be selected for driving, lowering the number of vehicles passing by. Constraint Eq. (18) indicates that users' cars increase with time, leading to the increase of vehicles passing on the road abreast of the improvement of economy and living standards. However, the number of vehicles passing on a road cannot exceed its capacity, which is ensured in constraint Eq. (19).

4.2.3 Pavement performance

The pavement performance is generally measured by the pavement condition index (PCI), which can be divided into five states according to the PCI value ranges [42], and corresponding to different maintenance measures [43]: preventive maintenance and proactive maintenance (repair), as shown in Table 1. The whole pavement performance can be calculated by applying the medium value of each PCI value range in five states, which can be expressed as:

$$PCI_R^t = 95 \times r_{s_1}^t + 85 \times r_{s_2}^t + 75 \times r_{s_3}^t + 65 \times r_{s_4}^t + 30 \times r_{s_5}^t, \quad (20)$$

where $PCI_R^t$ is the whole pavement performance in year *t* with $r_{s_j}^t (i = 1,2,\cdots,5)$ being the ratio of the maintenance mileage in state $s_j$ to the total maintenance mileage $TM$, which can be determined as follows:

$$r_{s_i}^t = \frac{M_{s_j}^t}{TM}, \quad (21)$$

where $M_{s_j}^t$ represents the maintenance mileage in state $s_j$ in year *t*.

**Table 1.** Pavement performance and maintenance measures

| Pavement state | PCI | Maintenance measure |
|---|---|---|
| Excellent ($s_1$) | 100-90 | |
| Good ($s_2$) | 90-80 | Preventive maintenance 1 (PM1) |
| Fair ($s_3$) | 80-70 | Preventive maintenance 2 (PM2) |
| Poor ($s_4$) | 70-60 | Repair 1 (R1) |
| Very poor ($s_5$) | < 60 | Repair 2 (R2) |

4.2.4 Maintenance measures

For predicting future pavement conditions, Markov chain (MC) is commonly applied [44, 45], by which future pavement conditions can be analyzed subject to initial pavement conditions with the state transition probability matrix (TPM). In [46, 47], the TPM is utilized to explicitly explain the uncertainty associated with pavement deterioration as it can describe the probability that a road pavement section will stay in its existing state and transit to another state at the beginning of the next year. Generally, the pavement state can become only deteriorating rather than upgraded to a better state unless maintenance measures are taken. Therefore, the predicted future pavement conditions are given by

$$\begin{bmatrix} M_{s_1}^{t} & M_{s_2}^{t} & M_{s_3}^{t} & M_{s_4}^{t} & M_{s_5}^{t} \end{bmatrix} = \begin{bmatrix} M_{s_1}^{ini} & M_{s_2}^{ini} & M_{s_3}^{ini} & M_{s_4}^{ini} & M_{s_5}^{ini} \end{bmatrix} \times \mathrm{TPM}$$

$$= \begin{bmatrix} M_{s_1}^{ini} & M_{s_2}^{ini} & M_{s_3}^{ini} & M_{s_4}^{ini} & M_{s_5}^{ini} \end{bmatrix} \times \begin{bmatrix} p_{s_1s_1}^{t} & p_{s_1s_2}^{t} & p_{s_1s_3}^{t} & p_{s_1s_4}^{t} & p_{s_1s_5}^{t} \\ 0 & p_{s_2s_2}^{t} & p_{s_2s_3}^{t} & p_{s_2s_4}^{t} & p_{s_2s_5}^{t} \\ 0 & 0 & p_{s_3s_3}^{t} & p_{s_3s_3}^{t} & p_{s_3s_5}^{t} \\ 0 & 0 & 0 & p_{s_4s_4}^{t} & p_{s_4s_5}^{t} \\ 0 & 0 & 0 & 0 & p_{s_5s_5}^{t} \end{bmatrix}, \tag{22}$$

where $M_{s_i}^{ini}$ is the initial mileage and $p_{s_is_j}^{t}$ is the transition probability form state $s_i$ to state $s_j$ in year *t*.

Preventive maintenance can extend the service life of the pavement by reducing its deterioration rate, but it cannot change the current pavement state, while proactive maintenance can improve the pavement performance by changing its state. The different maintenance skills of service providers may also affect the maintenance activities and the service life of the pavement. Therefore, the pavement maintenance activities can be defined as:

$$\begin{cases} PMM \times ME1 \times \frac{Sl_{av}^{p}}{Sl_{N_i^f}^{p}} & if\ PM1 \\ PMM \times ME2 \times \frac{Sl_{av}^{p}}{Sl_{N_i^f}^{p}} & if\ PM2 \\ PMM \times (Sl_{N_i^f}^{p} + (1 - Sl_{N_i^f}^{p}) \times p_{s_2s_2}^{t}) & if\ R1\ and\ Sl_{N_i^f}^{p} < Sl_{av}^{p} \\ PMM \times (1 - Sl_{N_i^f}^{p}) \times p_{s_2s_3}^{t}) & if\ R1\ and\ Sl_{N_i^f}^{p} < Sl_{av}^{p} \\ PMM \times 1.0 & if\ R1\ and\ Sl_{N_i^f}^{p} > Sl_{av}^{p} \\ PMM \times (Sl_{N_i^f}^{p} + (1 - Sl_{N_i^f}^{p}) \times p_{s_1s_1}^{t}) & if\ R2\ and\ Sl_{N_i^f}^{p} < Sl_{av}^{p} \\ PMM \times (1 - Sl_{N_i^f}^{p}) \times p_{s_1s_2}^{t}) & if\ R2\ and\ Sl_{N_i^f}^{p} < Sl_{av}^{p} \\ PMM \times 1.0 & if\ R2\ and\ Sl_{N_i^f}^{p} > Sl_{av}^{p}, \end{cases} \tag{23}$$

where $PMM$ is the pavement maintenance mileage performed, $ME1$ and $ME2$ represent the maintenance effectiveness of preventive measures PM1 and PM2, respectively, and the $Sl_{av}^{p}$ and $Sl_{N_i^f}^{p}$ represent the average skill level of all service providers and the skill level of service provider $N_i^f$ at period *p*, respectively.

4.3 The lower-level (service providers) profit optimization model

After the highway agency determines the pavement mileage to be maintained, the service provider as the follower rationally selects their serviced pavement mileage response to the decisions of the highway agency. The service providers' objectives often tend to maximize their individual total profits coming from maintenance income and service skill cost. Therefore, the multi-objective optimization model for the service provider $N_i^f$ is as follows:

$$U_i^f = \max \sum_{t=1}^{T} (C_{N_i^f}^t - SC_{N_i^f}^t) \tag{24}$$

subject to (12) and:

$$SC_{N_i^f}^t = \sum_{j=1}^{5} (MSlC_{s_j N_i^f}^t \times M_{s_j N_i^f}^t), \tag{25}$$

where the $C_{N_i^f}^t$ is maintenace income of service provider $N_i^f$ in year *t*, $SC_{N_i^f}^t$ stands for service skill cost, and $MSlC_{s_j N_i^f}^t$ represents the unit maintenance skill cost.

Equation (24) indicates the objectives of service providers are to maximize their profits. In the constraints, Eq. (25) is service skill cost of the service provider $N_i^f$, relating to its maintenance skills across the five states of pavements.

4.4 Bilevel mathematical model

The conflicts and interactions among the highway agency and service providers are reflected in the influence of highway agency's decision $(M_{N_i^f}^{lt})$ on the service providers' decisions $(M_{s_j N_i^f}^t, MC_{s_j N_i^f}^t)$, and vice versa. For resolving the conflicts and achieving a satisfactory solution, the problem is expressed mathematically in a bilevel mathematical model for all stakeholders to make decisions based on the above game models with multi-objective optimization. In summary, the bilevel mathematical model is formulated as follows:

$$\mathrm{U}^l(m^t) = F(\min C, \min UPDs) = \sum_{t=1}^{T} (TI^t - SA^t - C^t)$$

$$\text{s.t.} \begin{cases} (16) - (19), \text{ and } (23) \\ U_i^f = \max \sum_{t=1}^{T} (C_{N_i^f}^t - SC_{N_i^f}^t) \\ (12) - (14), \text{ and } (25). \end{cases} \tag{26}$$

From the built bilevel mathematical model, the maintenance mileage is the common decision variable of the two game models and corresponding multi-objective optimization conditions so as they render as interdependent. The bilevel mathematical model is a multi-player Stackelberg-Nash game for the highway agency and service providers. The goal for the leading highway agency is to obtain optimal solutions incorporating all the objectives, and for following service providers is to obtain a Nash equilibrium solution to achieving their own profits among all service providers. For all decision-makers, the balance is finally attained to satisfy their individual objectives. Therefore, the Stackelberg-Nash equilibrium solution could be the optimal solution of the bilevel mathematical model with an optimistic expectation of the highway agency as well as service providers.

To evaluate the profits obtained, the profits obtained each year is converted to net present value (NPV), the principle of which is expressed in the following equation:

$$\text{NPV} = \sum_{t=1}^{T} \frac{Pf^{lt} \text{ or } Pf^{N_i^f t}}{(1+r_d)^t}, \tag{27}$$

where $Pf^{lt}$ and $Pf^{N_i^f t}$ represent the total profits respectively for the leader and the follower $N_i^f$, and $r_d$ is the discount rate.

## 4.5 Solution algorithm

The multi-player pavement maintenance problem has been brought into that of finding the Stackelberg-Nash equilibrium solution. However, each level of the proposed bilevel mathematical model belongs to the class of nondeterministic polynomial (NP) hard problem [48], which is difficult to find a global optimal solution. As mentioned above, heuristic-based algorithms have been proven to be an effective method to solve NP hard problems. Therefore, to obtain the optimal solutions, a heuristic BLPSO algorithm is proposed here.

### 4.5.1 Basics of PSO

PSO is a population-based optimization tool for solving various complex problems in optimization [49, 50]. PSO simulates the movement of those particles to search the optimal position in the search space. The particles have velocities that can be dynamically adjusted according to the experience of their own and of their companions to change their position in the search space, and record its previous best position as personal best (pbest) in the search space. The PSO can keep the best value and position in particles of the swarm during the simulate process, which is called global best (gbest). Each particle moves toward its best previous position and toward the best particle in the whole swarm.

Let $X=(x_i^l(k),x_i^f(k))$ represent the position vector for each particle of the leader and follower, respectively, $V=(v_i^l(k),v_i^f(k))$ is the position change or velocity vector for each particle correspondingly. Suppose that in the search space, for updating the velocity and position respectively, the velocity and position of the $i$-th particle for the next iteration ($k+1$) can be expressed as follows:

$$v_i(k+1)=w(k+1)\times v_i(k)+c_p\times r_p\times(pbestx_i(k)-x_i(k))+c_g\times r_g\times(gbestx_i(k)-x_i(k)) \tag{28}$$

$$x_i(k+1)=x_i(k)+v_i(k+1), \tag{29}$$

where $v_i(k+1)$ is the updated velocity at iteration $k+1$ for $i$-th particle, $x_i(k+1)$ is the updated current position at iteration $k+1$ for $i$-th particle, $c_p$ and $c_g$ are respectively two acceleration coefficients called learning factors, namely cognitive learning factor and social learning factor, and $r_p$ and $r_g$ are uniformly disturbed random numbers within 0 and 1. The weight $w(k+1)$, describing the inertia of velocity influencing the ($k+1$)-th iteration, can be expressed as:

$$w(k+1)=w_{end}-(w_{end}-w_{ini})\times\frac{max\_iteration-(k+1)}{max\_iteration}, \tag{30}$$

where $w_{ini}$ is the initial inertia weight and $w_{end}$ is the end inertia weight when iterating to the maximum evolution algebra. The inertia weights $w(k)$ is set as increasing with the iterations, while weights $w_{ini}$ and $w_{end}$ are assigned to 0.1 and 0.9, respectively, as the reasonable values [51, 52]. A generic PSO is depicted in Fig. 2.

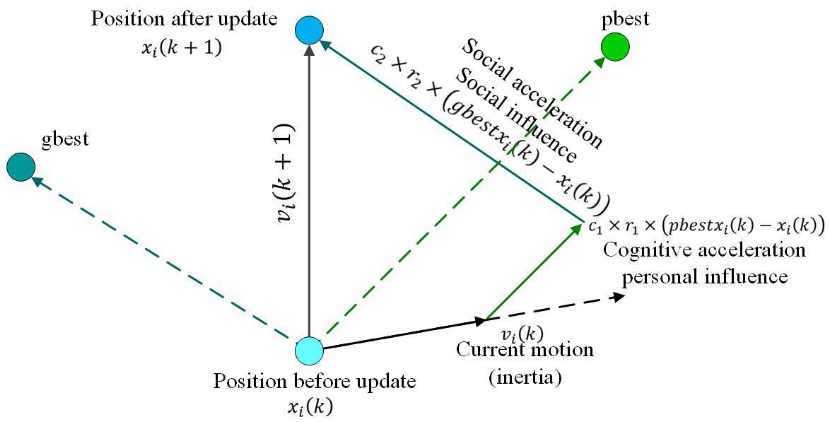



**Fig. 2.** Illustration of PSO.

4.5.2 Fitness value

The fitness value is of great importance to evaluate the particle in the swarm for the objective function on each level. The fitness value of the upper-level and lower-level models can be expressed respectively as:

$$\mathrm{Fitness}^{l} = \mathrm{U}^{l}(m^{t}) \tag{31}$$

$$\mathrm{Fitness}^{\mathrm{f}}=\sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{U}_{\mathrm{i}}^{\mathrm{f}}. \tag{32}$$

From the above formulation, a selection process can be carried out to obtain eligible particles. As the designed fitness value is of the maximization type, the particle has the larger fitness value is selected as an eligible particle. The personal best and global best of the upper-level model can be updated respectively as follows:

Update $\mathrm{P}^{\mathrm{l}}(\mathrm{k})=\mathrm{x}_{\mathrm{i}}^{\mathrm{l}}(\mathrm{k})$, if $\mathrm{Fitness}^{\mathrm{l}}(\mathrm{x}_{\mathrm{i}}^{\mathrm{l}}(\mathrm{k}))> \mathrm{Fitness}^{\mathrm{l}}(\mathrm{x}^{\mathrm{l}}(\mathrm{k}\text{-}1))$.

Update $\mathrm{G}^{\mathrm{l}}(\mathrm{k})=\mathrm{P}^{\mathrm{l}}(\mathrm{k})$, if $\mathrm{Fitness}^{\mathrm{l}}(\mathrm{P}^{\mathrm{l}}(\mathrm{k}))> \mathrm{Fitness}^{\mathrm{l}}(\mathrm{P}^{\mathrm{l}}(\mathrm{k}\text{-}1))$.

For the lower-level model, the personal best and global best can be updated as follows:

Update $\mathrm{P}^{\mathrm{N}_1^{\mathrm{f}}}(\mathrm{k})=\mathrm{x}_{\mathrm{i}}^{\mathrm{N}_1^{\mathrm{f}}}(\mathrm{k})$, $\mathrm{P}^{\mathrm{N}_2^{\mathrm{f}}}(\mathrm{k})=\mathrm{x}_{\mathrm{i}}^{\mathrm{N}_2^{\mathrm{f}}}(\mathrm{k})$, $\cdots$, $\mathrm{P}^{\mathrm{N}_3^{\mathrm{f}}}(\mathrm{k})=\mathrm{x}_{\mathrm{i}}^{\mathrm{N}_3^{\mathrm{f}}}(\mathrm{k})$, if $\mathrm{Fitness}^{\mathrm{f}}(\mathrm{x}_{\mathrm{i}}^{\mathrm{N}_1^{\mathrm{f}}}(\mathrm{k}), \mathrm{x}_{\mathrm{i}}^{\mathrm{N}_2^{\mathrm{f}}}(\mathrm{k}),\cdots, \mathrm{x}_{\mathrm{i}}^{\mathrm{N}_{\mathrm{n}}^{\mathrm{f}}}(\mathrm{k}))> \mathrm{Fitness}^{\mathrm{f}}(\mathrm{x}_{\mathrm{i}}^{\mathrm{N}_1^{\mathrm{f}}}(\mathrm{k}\text{-}1), \mathrm{x}_{\mathrm{i}}^{\mathrm{N}_2^{\mathrm{f}}}(\mathrm{k}\text{-}1), \cdots, \mathrm{x}_{\mathrm{i}}^{\mathrm{N}_{\mathrm{n}}^{\mathrm{f}}}(\mathrm{k}\text{-}1))$.

Update $\mathrm{G}^{\mathrm{N}_1^{\mathrm{f}}}(\mathrm{k})=\mathrm{P}^{\mathrm{N}_1^{\mathrm{f}}}(\mathrm{k})$, $\mathrm{G}^{\mathrm{N}_2^{\mathrm{f}}}(\mathrm{k})=\mathrm{P}^{\mathrm{N}_2^{\mathrm{f}}}(\mathrm{k}), \cdots$, $\mathrm{G}^{\mathrm{N}_{\mathrm{n}}^{\mathrm{f}}}(\mathrm{k})=\mathrm{P}^{\mathrm{N}_{\mathrm{n}}^{\mathrm{f}}}(\mathrm{k})$, if $\mathrm{Fitness}^{\mathrm{f}}(\mathrm{P}^{\mathrm{N}_1^{\mathrm{f}}}(\mathrm{k}),\mathrm{P}^{\mathrm{N}_2^{\mathrm{f}}}(\mathrm{k}),\cdots,\mathrm{P}^{\mathrm{N}_{\mathrm{n}}^{\mathrm{f}}}(\mathrm{k})) > \mathrm{Fitness}^{\mathrm{f}}(\mathrm{P}^{\mathrm{N}_1^{\mathrm{f}}}(\mathrm{k}\text{-}1), \mathrm{P}^{\mathrm{N}_2^{\mathrm{f}}}(\mathrm{k}\text{-}1), \cdots, \mathrm{P}^{\mathrm{N}_{\mathrm{n}}^{\mathrm{f}}}(\mathrm{k}\text{-}1))$.

### 4.5.3 BLPSO for the Stackelberg-Nash equilibrium

To obtain the overall equilibria of the Stackelberg game and the Nash game, a framework of BLPSO is proposed as shown in Fig. 3. The right part therein shows the solution procedure to solve the upper-level programming problem, whereas the left illustrates the analytical algorithm to solve the lower-level programming problem. The detailed procedure of the proposed BLPSO algorithm for pavement maintenance is as follows:

(1) Initialize the parameters and feasible decision strategies of the highway agency

In the upper-level model, parameters of the upper-level PSO are first initialized, and each particle is assigned to a random position as the total maintenance mileage for each service provider. The random positions of the upper-level model as feasible decision strategies of the highway agency are then input into the lower-level model to find the optimal solutions of all service providers.

(2) Optimize service providers' decision strategies corresponding to the highway agency's

decision strategies

After determining the highway agency's decision strategies, the next step is to obtain the lower-level Nash equilibrium solution by applying the followed steps.

Step 1: Initialize parameters of the lower-level PSO, and generate a random position for each particle as the maintenance mileage in different pavement maintenance activities at different years for the service provider as decision strategies.

Step 2: Calculate the profit of each service provider to obtain the lower-level fitness value and update the decision strategies of each service provider if the calculated fitness value is greater than the previous fitness value.

Step 3: Update the velocity and position of each particle for adjusting the decision strategies of each service provider until reaching the termination condition of the lower-level model.

Step 4: Obtain positions of the lower-level model as optimal decision strategies of all service providers are finally input into the upper-level model.

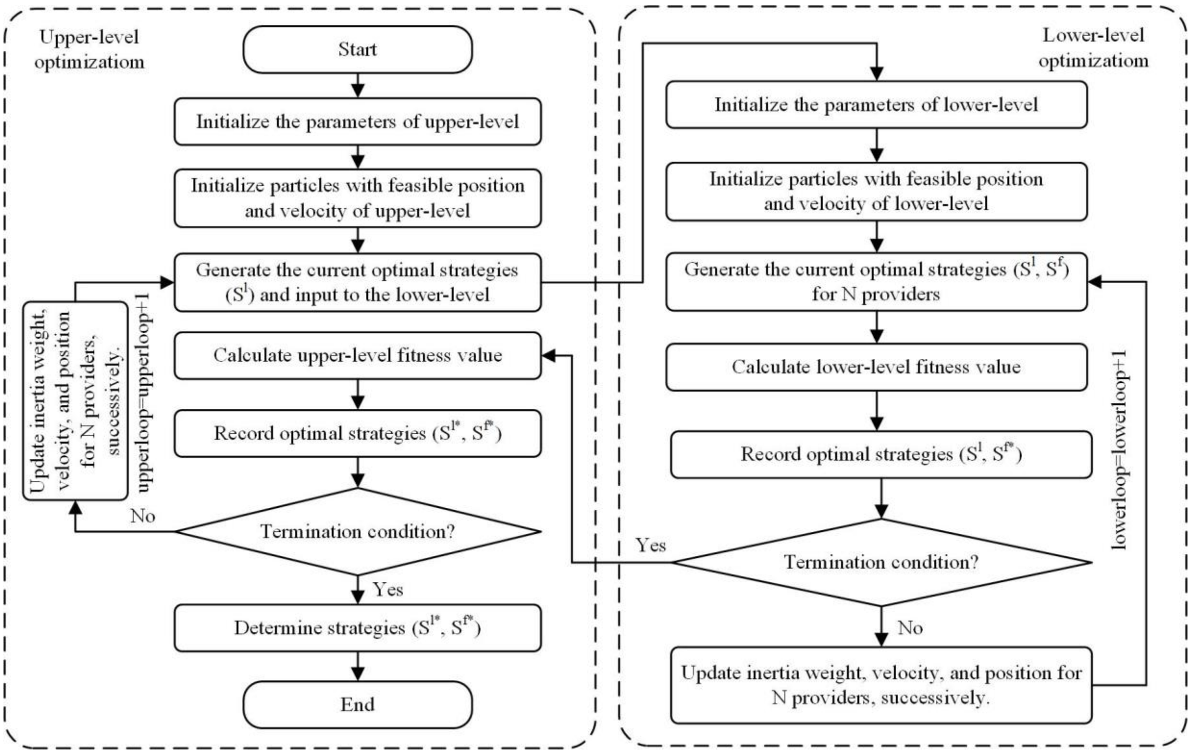



**Fig. 3.** BLPSO algorithm framework.

(3) Optimize the highway agency's decision strategies based on service providers' decision strategies

According to service providers' decision strategies, the upper-level fitness value can be calculated. If the upper-level fitness value is greater than the previous fitness value, the decision strategies of the highway agency and service providers are respectively recorded and updated. For optimizing the highway agency's decision strategies, the velocity and position of each particle are updated to adjust the decision strategies of the highway agency until up reaching the termination condition of the upper-level model.

(4) Determine the optimal decision strategies of the highway agency and service providers.

If the termination condition of the upper-level model is met, the interactive process is not continuous, the optimal decision strategies of the highway agency and service providers are output, and the final decision strategies not only meet the highway agency's requirements but also satisfy service providers' interests. Thereby, Stackelberg-Nash equilibrium solutions for multi-player pavement maintenance problems are obtained.

## 5. Case Study

A practical application case is used to explore the pavement maintenance problem for demonstrating the practicality and efficiency of the proposed methodology. To further examine its advantages, a comparative study is carried out using the traditional single-level method considering a one-player decision-maker.

### 5.1 Case description

A highway project 128 km located in the Zhejiang province in China is applied to demonstrate the proposed methodology. The highway project with a four-lane interstate is planned for a maintenance horizon of 20 years excluding 3 years of construction duration. To facilitate adjustment of maintenance strategies during the long-term maintenance horizon, the maintenance horizon is divided into four periods and each period consists of five years. The initial unit maintenance procurement cost and unit maintenance management cost of each maintenance activity for each service provider at each period are listed in Table 2 and Table 3, respectively. The maximum and minimum service capacities for service suppliers are presented in Table 4 while the skill levels for service suppliers at different periods are shown in Table 5. The subsidy from the government and the maintenance effectiveness of PM1 and PM2 are provided in Table 6 and other related maintenance parameters are given in Table 7. The initial condition of the highway pavement and the state transition probability matrix (TPM) of the highway are obtained as shown in Eqs. (33) and (34), respectively.

**Table 2.** Initial unit maintenance procurement cost for service suppliers over periods.

| Period | Supplier | PM1 | | | PM2 | | R1 | | R2 | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | C2 | C3 | C4 | C3 | C4 | C4 | C5 | C4 | C5 |
| 1 | A | 2.73 | 9.23 | 13.26 | 12.23 | 18.26 | 77.5 | 80.2 | 107.9 | 110.97 |
| | B | 2.79 | 9 | 13 | 11.88 | 18.65 | 77.88 | 82 | 106.3 | 112.046 |
| 2 | A | 7.5 | 14.2 | 19.8 | 17.9 | 24.7 | 105.8 | 111.43 | 142.1 | 154.22 |
| | B | 8 | 14.63 | 19.62 | 18.83 | 26.26 | 105.67 | 110.83 | 143.63 | 153.6 |
| 3 | A | 14.3 | 19.3 | 25.3 | 22.7 | 30 | 143.2 | 149.22 | 189.45 | 199.22 |
| | B | 14.4 | 19 | 24.9 | 22 | 29.8 | 142.1 | 150.3 | 188.73 | 200.43 |
| 4 | A | 18.6 | 24.9 | 33.4 | 29.55 | 38.93 | 184.1 | 194.33 | 252.33 | 264.4 |
| | B | 18.2 | 24.33 | 33.23 | 29.21 | 37.66 | 185.74 | 194.13 | 251.26 | 264.68 |

Note: All costs expressed in $10^4$ Chinese Yuan (CNY).

### 5.2 Parameters sensitivity analysis for BLPSO

The parameters in heuristic algorithms are important factors that can significantly influence the performance of BLPSO proposed for pavement maintenance. To gain further insights into the influence, a sensitivity analysis is conducted. To select parameter values, the same parameter values are initially set as in previous research, the cumbersome way is to rely on a trial-and-error procedure. However, these methods do not ensure that the parameter values set are effective and efficient. Fortunately, the orthogonal experiment method has been proven to be effective and efficient for selecting appropriate parameter values through small-scale experiments by an orthogonal array [51, 53, 54]. The remarkably successful applications of the orthogonal experiment method motivate the authors to examine its performance in parameter values selection of BLPSO for pavement maintenance.

**Table 3.** Initial unit maintenance management cost for service suppliers over periods.

| Period | Supplier | PM1 | | | PM2 | | R1 | | R2 | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | C2 | C3 | C4 | C3 | C4 | C4 | C5 | C4 | C5 |
| 1 | A | 2.1 | 7.1 | 10.5 | 8.33 | 13.34 | 65.3 | 67.4 | 82.37 | 85.36 |
| | B | 2.13 | 7 | 10.5 | 8.6 | 14.5 | 66 | 70.1 | 80 | 85.42 |
| 2 | A | 6.1 | 11.38 | 16.5 | 13.87 | 18.99 | 89.3 | 93.1 | 110.8 | 120.3 |
| | B | 6.4 | 12.1 | 15.74 | 15.2 | 20.34 | 88.33 | 92.66 | 113.3 | 120.8 |
| 3 | A | 12.2 | 16.2 | 20.4 | 18.2 | 24 | 123.43 | 128.43 | 153.1 | 160.2 |
| | B | 12.4 | 15.6 | 20.4 | 17.3 | 23.4 | 122.2 | 129.3 | 152.64 | 160.7 |
| 4 | A | 15.5 | 21.4 | 29.12 | 24.41 | 32.44 | 162.3 | 170.54 | 212.33 | 222.46 |
| | B | 15.3 | 20.5 | 28.7 | 23.5 | 31.2 | 163.4 | 171.3 | 211 | 223.4 |

Note: All costs expressed in $10^4$ CNY.

**Table 4.** Service providers' service capacity over periods.

| Supplier | Capacity | Period 1 | Period 2 | Period 3 | Period 4 |
|---|---|---|---|---|---|
| A | minimum | 35 | 40 | 30 | 35 |
| | maximum | 80 | 90 | 105 | 100 |
| B | minimum | 30 | 40 | 35 | 30 |
| | maximum | 100 | 100 | 95 | 90 |

Note: All mileages expressed in km.

In the proposed BLPSO, six parameters need to be controlled for optimal values. Based on the selected parameter values from previous research and the trial and error procedure, three-level factors of each parameter are set. As to the change of each parameter, the increase/decrease value for $P^l$ and $P^f$ is 20, and for $c_p^l$, $c_p^f$, $c_g^l$, and $c_g^f$ is 0.2 as shown in Table 8, and suitably for that arrangement the Taguchi's orthogonal array $L_{18}(3^6)$ is constructed. To further determining appropriate parameter values for small-scale experiments, relatively smaller $P^l$ and $P^f$, with relatively smaller $c_p^l$ and $c_p^f$ [34] are applied to set as a combination. The built experiments based on parameter value combinations are shown for the first 6 rows in Table 9. Thereafter, several trial runs of BLPSO for setting each parameter value combination are performed until the maximum iterations are reached, the computational results, and average computing time, respectively, are obtained as presented in Table 9, based on which the best parameter value combination can be selected. Compared with various experiments with different parameter combinations, the first experiment, $P^l$=20, $P^f$=30, $c_p^l$=1.6, $c_p^f$=1.4, $c_g^l$=1.8, $c_g^f$=1.6, is considered the best NPV while the fourth experiment, $P^l$=40, $P^f$=50, $c_p^l$=2.0, $c_p^f$=1.8, $c_g^l$=1.8, $c_g^f$=1.6, obtain the greatest average NPV. The computing time required for 20 $P^l$ and 30 $P^f$ is about 1 day, given that the higher the number of particles the more processing time in average required. Therefore, by fully considering the profit and computing time, the first combination shown in Table 9 is selected as the optimal parameters for a feasible solution to the dynamic long-term problem of multi-player pavement maintenance.

**Table 5.** Service suppliers' skill level over periods.

| Supplier | Period 1 | Period 2 | Period 3 | Period 4 |
|---|---|---|---|---|
| A | 0.8 | 0.9 | 1.1 | 1.1 |
| B | 1.1 | 1.2 | 1 | 0.9 |

**Table 6.** Unit management cost for service providers and the maintenance effectiveness over periods.

| Period | Cost | Period | Cost | Maintenance measures | Maintenance effectiveness |
|---|---|---|---|---|---|
| 1 | 800 | 3 | 1300 | PM1 | 0.8 |
| 2 | 1000 | 4 | 1500 | PM2 | 0.7 |

Note: All costs expressed in $10^4$ CNY.

**Table 7.** Other related maintenance parameters of the bilevel mathematical model.

| $r_c$ | $r_d$ | TR | $UTw_{min}$ | $V^{ini}$ | $r_v$ | $V_{max}$ |
|---|---|---|---|---|---|---|
| 5% | 3.5% | 0.27 CNY/(km· vehicle) | 0.2 | 2.3 million | 0.6 million | 10 million |

$$\left[M_{s_1}^{ini} \quad M_{s_2}^{ini} \quad M_{s_3}^{ini} \quad M_{s_4}^{ini} \quad M_{s_5}^{ini}\right] = [122 \quad 6 \quad 0 \quad 0 \quad 0] \tag{33}$$

$$
\text{TPM}=\begin{bmatrix} 0.8267 & 0.1733 & 0 & 0 & 0 \\ 0 & 0.7069 & 0.2931 & 0 & 0 \\ 0 & 0 & 0.6334 & 0.3666 & 0 \\ 0 & 0 & 0 & 0.5813 & 0.4187 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}. \tag{34}
$$

**Table 8.** Parameters and their levels selected for PMBLPSO model.

| Level | $P^l$ | $c_p^l$ | $c_g^l$ | $P^f$ | $c_p^f$ | $c_g^f$ |
|---|---|---|---|---|---|---|
| 1 | 20 | 1.6 | 1.8 | 30 | 1.4 | 1.6 |
| 2 | 40 | 1.8 | 2.0 | 50 | 1.6 | 1.8 |
| 3 | 60 | 2.0 | 2.2 | 70 | 1.8 | 2.0 |

**Table 9.** The parameter value combinations and parameter sensitivity analysis for PMBLPSO.

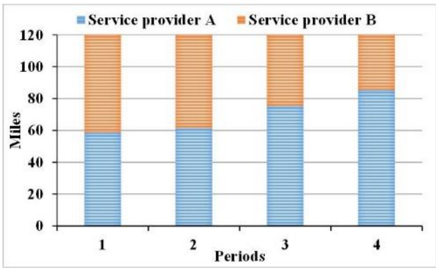
| Experiment number | $P^l$ | $c_p^l$ | $c_g^l$ | $P^f$ | $c_p^f$ | $c_g^f$ | Fitness value | | NPV | | ACT |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | Best | Average | Best | Average | |
| 1 | 20 | 1.6 | 1.8 | 30 | 1.4 | 1.6 | 222201.36 | 214054.13 | 156729.62 | 152636.04 | 1.01 |
| 2 | 20 | 1.8 | 2.2 | 30 | 1.6 | 2.0 | 213155.93 | 211451.45 | 151425.69 | 150871.37 | 0.95 |
| 3 | 40 | 1.8 | 2.0 | 50 | 1.6 | 1.8 | 220801.74 | 214775.30 | 156052.97 | 153022.89 | 2.90 |
| 4 | 40 | 2.0 | 1.8 | 50 | 1.8 | 1.6 | 221969.34 | 216665.97 | 156214.11 | 154355.00 | 2.92 |
| 5 | 60 | 1.6 | 2.0 | 70 | 1.4 | 1.8 | 220204.15 | 214728.65 | 156486.53 | 153625.41 | 6.00 |
| 6 | 60 | 2.0 | 2.2 | 70 | 1.8 | 2.0 | 213639.68 | 210906.40 | 152178.76 | 150824.56 | 5.99 |

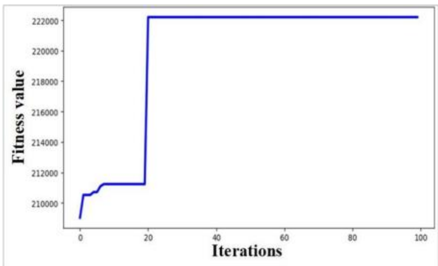
Note: ACT = average computing time (d).

## 5.3 Computational Results

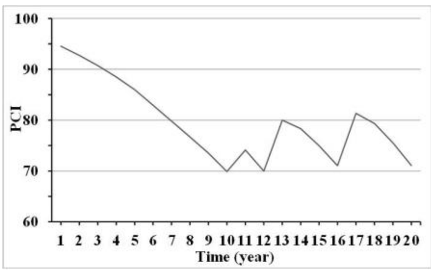
According to the proposed bilevel mathematical model shown in Eq. (26), the optimization process could be utilized with the developed BLPSO described in Fig. 3, from which the optimal computational results are obtained as presented in Fig. 4. Based on the computational results, the inference from the results can be summarized below.

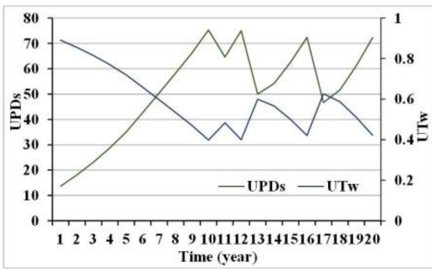
Figure 4(a) shows the highway agency's decision on the maintenance mileage allocated to service providers at different periods, and the maintenance mileage for service provider A is 58.74 km, 61.52 km, 75.38 km, and 85.52 km, respectively. Figure 4(b) indicates the detailed distribution of the fitness values of the upper-level model, wherein it can be seen that the fitness values gradually increased as the iteration numbers increased before reaching the convergence iterations (20 iterations). Figure 4(c) demonstrates that the change of PCI value owing to the implementation of maintenance measures while Fig. 4(d) indicates the users' pavement dissatisfaction on the road pavement condition and the user's travel willingness. From Figs. 4(c) and 4(d), it can be observed that the pavement performance has an obvious influence on the users' pavement dissatisfaction and thus the user's travel willingness. From Fig. 4(e) shows the toll income and the highway agency's profit over the maintenance horizon, it is clear that the toll income directly affects the highway agency's profit, and to some extent also pavement performance, which in turn drives service providers to take continuous measures to maintain the pavement. Therefore, the profits for service providers from the performed maintenance measures can be obtained, as depicted in Fig. 4(f). As to the net present value defined in (27), the total NPVs of the highway agency and service provider A, B can be seen in Fig. 4(g) as156729.62 $\times 10^4$ CNY, 2646.71 $\times 10^4$ CNY, and 1948.20 $\times 10^4$ CNY, respectively. Certainly, these are satisfactory profits for the highway agency and service provider A, B.



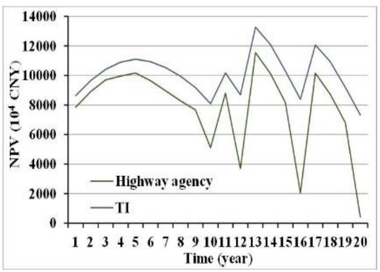



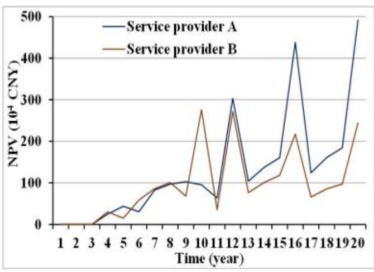

(a) Maintenance mileage allocated. (b) Equilibrium fitness of upper-level model.

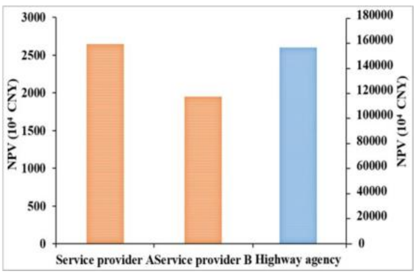



(c) PCI during the maintenance horizon. (d) Changes in UPDs and UTw.




(e) NPVs of highway agency and TI. (f) NPVs of service providers. (g) Total NPVs of service providers.

**Fig. 4.** Computational results.

In general, the computational results approved by the decision-makers demonstrated that their strategies around the road pavement project have an impact on pavement performance and the profits over the maintenance horizon. It is indicated that the proposed bilevel mathematical model is able to find multi-player maintenance strategies for the dynamic pavement maintenance in long terms, which could serve as a valuable reference to help all stakeholders make reasonable decisions over the maintenance horizon.

### 5.4 Model comparison

To illustrate the advantages of the proposed bilevel mathematical model for resolving conflicts and interactions of multi-player decision-makers on dynamic long-term multi-objective pavement maintenance problem, a comparison analysis is conducted between the proposed model and a single-level model. In the single-level model, the highway agency mainly considers the maintenance mileage regardless of service providers' operations. As a conventional centralized model, the single-level model seeks an individual optimal solution while implementing the decisions made by the highway agency, neglecting the conflicts and interactions among service providers. Specifically, in the single-level model, the profits pursued by service providers do not affect the total profit pursued by the highway agency, hence these objective functions of service providers are not included in the optimization, while the constraints remain the same as in (26). As such, the constructed single-level model can be expressed as:

$$\mathrm{U}^{l}(m^{t}) = F(\min C, \min UPDs) = \sum_{t=1}^{T}(TI^{t} - SA^{t} - C^{t}) \tag{35}$$
$$\text{s.t. } (12) - (14), (16) - (19), (23), \text{and } (25)\,.$$

Figure 5 illustrates the comparison between results obtained by the bilevel mathematical model and the single-layer model. Learning from the results, it can be seen that the NPVs obtained using a single-level model are inferior to those using the bilevel mathematical model, which means that although the single-level model can solve the problem and achieve objective profits, it results in unbalancing development across the entire pavement maintenance field. For the highway agency, the single-level model only considers the leader's profits and ignores the service providers, resulting in incomprehensive results. Moreover, the users' pavement dissatisfaction using the single-level model could be greater than that using the bilevel mathematical model (i.e. the users' travel willingness could be less than that obtained from the bilevel mathematical model), as shown in Fig. 6. Although the single-level model for the dynamic long-term pavement maintenance requires a shorter time to compute (about 25 minutes), resolving the conflicts and presenting a win-win situation among decision-makers are more important to ultimately obtain a satisfactory solution for all parties involved. As can be seen, applying the bilevel mathematical model achieves higher profits, the NPVs of service provider A and B is increased by 49.52% and 38.46%, respectively, while that of highway agency is also improved. Therefore, it can be concluded that the proposed bilevel mathematical model is more reasonable and suitable for optimizing pavement maintenance.

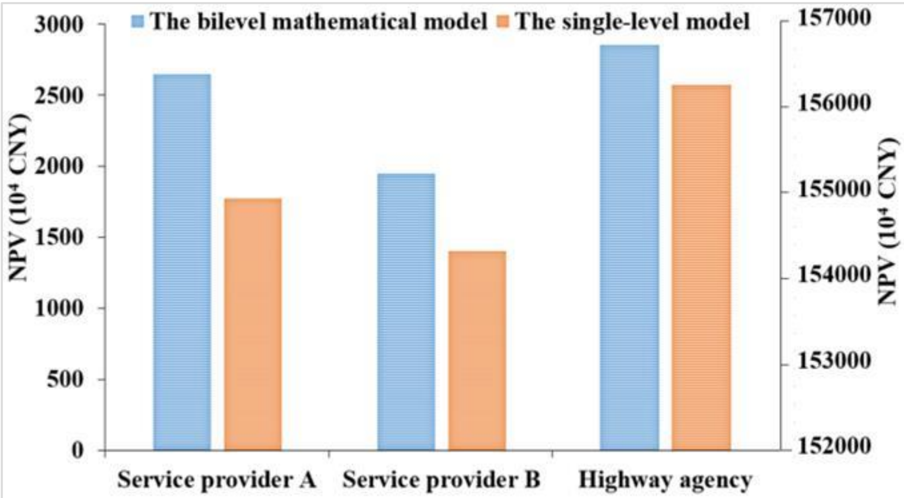



**Fig 5.** The result comparison.

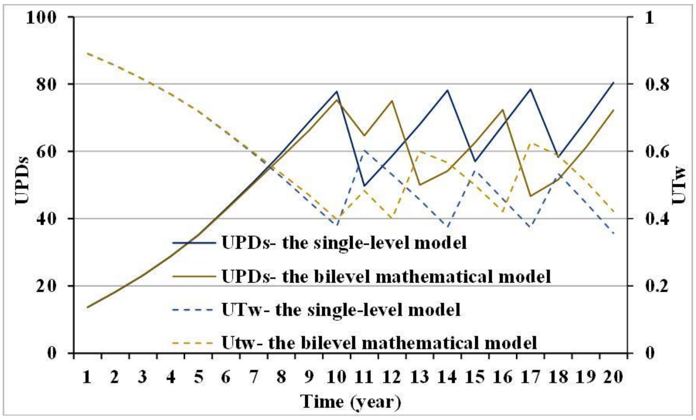



**Fig. 6.** Comparison of the users' pavement dissatisfaction and travel willingness.

### 5.5 Managerial implications

In the practical pavement maintenance management, the maintenance problem can affect the pavement condition, user's pavement dissatisfaction, users' travel willingness, and toll income. The proposed bilevel mathematical model offers a scientifically comprehensive tool to handle the pavement maintenance problem for reducing the occurrence of losses as much as possible and presenting a win-win situation for efficient maintenance operations. A number of managerial implications can be outlined as below:

(1) The inherent conflicts and complex interactions among decision-makers should be taken into account in formulating the pavement maintenance problem into mathematical models for further understanding their complexity, to obtain satisfactory maintenance strategies.

(2) The decision variables should be determined as the basic step for modeling mathematical models, which simultaneously considers the requirements and restrictions of the leader and followers modeled in the objective functions and constraints, respectively.

(3) The developed bilevel mathematical model can facilitate the vertical Stackelberg game among the highway agency and service providers, and incorporate the horizontal Nash game among all service providers. Simultaneously, the model has the ability to analyze and evaluate user's pavement dissatisfaction and users' travel willingness over the maintenance horizon.

(4) In the proposed bilevel mathematical model, the maintenance service providers are more beneficial than the highway agency because all service providers have opportunities to game with the highway agency for obtaining more profits, which could lead to more service providers willing to participate in the pavement maintenance, thereby improving the quality and efficiency of pavement maintenance in the long-term practical application.

(5) The proposed bilevel mathematical model, as a good example for modeling, can be extended to many other similar management problems by implementing minor modifications, such as supply chain management, electric power system maintenance, construction site layout and security planning, and so on.

## 6. Conclusions

This research proposes a bilevel mathematical model to find multi-player maintenance strategies for dynamic long-term pavement maintenance. A bilevel particle swarm optimization algorithm based on the Stackelberg-Nash game method is utilized to solve the bilevel mathematical model and determine optimal maintenance strategies for all decision-makers. For verifying the practicality and efficiency of the proposed bilevel mathematical model, a case study is presented. The main features and findings of this research are summarized as follows: (i) The proposed bilevel mathematical model integrates the conflicts and interactions among the highway agency and service providers into the decision-making process, (ii) For achieving the overall satisfactory balance among decision-makers, this research creatively develops a multi-objective Stackelberg-Nash game method to determine the optimal strategies for all parties involved, (iii) To deal with the inherent uncertainties of the pavement under environmental factors and traffic loads and better reflect the real-world pavement condition, the Markov chain is employed for predicting future pavement conditions, (iv) To obtain the appropriate parameter values of BLPSO, an orthogonal experiment method and parameter setting principle are utilized, a sensitivity analysis for BLPSO is conducted via small-scale experiments, (v) The proposed bilevel mathematical model is successfully applied for demonstrating its viability and effectiveness in a practical case, for which a comparison with a single-level model is conducted for illustrating its feasibility and comprehensiveness, and (vi) The proposed bilevel mathematical model can serve as a promising tool for the highway agency and service providers to make reasonable decisions on the dynamic long-term pavement maintenance, and moreover be extended to similar problems. Future work will be directed to address issues on automated collection of input data, application of the proposed model for more highway projects with larger maintenance horizon, and improvement of computational efficiency and latency reduction.

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