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Optimal prioritisation of asphalt pavement maintenance using gray realation analysis and cost-benefit analysis

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Original research paper

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Pavement maintenance prioritisation, which considers both quality and cost, is an important decision-making problem. The common approach involves the prioritisation of road repairs with more extensive surface damages but this does not always align with the actual repair needs. To address this, a method based on the grey relation analysis theory was introduced to evaluate pavement performance. This method was employed to determine the optimal maintenance time for asphalt pavements. Once the sequence was established, the ideal maintenance schedule for the pre-maintenance sections was determined using a cost–benefit model. This evaluation method is particularly useful for quantitative analyses of the influences of pavement age and traffic volume on pavement performance parameters. The results demonstrate that grey relation sorting effectively weighs the factors and provides rankings for road segments requiring maintenance. A cost–benefit analysis model was used to assess the maintenance sections. This model can guide decisions regarding pre-maintenance sections and assess pavement conditions, thus resulting in outcomes that align better with real-world situations and human judgment. These findings are expected to be valuable for the long-term maintenance of asphalt pavements.

Key words:

pavement maintenance, grey relation analysis, pavement condition index, pavement quality evaluation, optimisation model

Izvorni znanstveni rad

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Optimalno određivanje prioriteta održavanja asfaltnih kolnika primjenom sive realcijske analize te analize troškova i koristi

Određivanje prioriteta održavanja kolnika, što uzima u obzir i kvalitetu i cijenu, važan je problem u donošenju odluka. Uobičajeni pristup uključuje određivanje prioriteta popravaka na cesti s većim površinskim oštećenjima, ali to nije uvijek u skladu sa stvarnim potrebama popravka. Kako bi se to riješilo, uvedena je metoda temeljena na teoriji sive relacije za procjenu performansi kolnika. Tom se metodom određuje optimalno vrijeme održavanja asfaltnih kolnika. Nakon što je slijed postavljen, idealan raspored održavanja za dionice prije održavanja određen je pomoću modela troškova i koristi. Ova metoda procjene posebno je korisna za kvantitativne analize utjecaja starosti kolnika i prometnog opterećenja na parametre izvedbe kolnika. Rezultati pokazuju da primjena sive relacijske analize učinkovito prosuđuje čimbenike i rangira dijelove cesta koji zahtijevaju održavanje. Za procjenu održavanja dionica korišten je model analize troškova i koristi. Taj model može usmjeravati odluke u vezi s dionicama prije održavanja i procijeniti uvjete kolnika, što rezultira ishodima koji su bolje usklađeni sa situacijama u stvarnom svijetu i ljudskom prosudbom. Očekuje se da će ovi nalazi biti vrijedni za dugoročno održavanje asfaltnih kolnika.

Ključne riječi:

održavanje kolnika, siva relacijska analiza, indeks stanja kolnika, procjena kvalitete kolnika, model optimizacije

1. Introduction

Asphalt pavements are extensively used in highway construction in many countries because of their convenient maintenance and comfortable driving. If the rapid growth of the pavement maintenance industry is to be sustained, an adequate budget must be set aside to maintain pavements in good condition; accordingly, the lack of budget funds is a major obstacle to pavement maintenance. The use of limited maintenance funds to optimise road networks has gradually become an urgent problem for highway management departments at all levels. Currently, numerous research efforts are expended on pavement prediction using the existing pavement condition index [1-3]. However, depending on the situation, maintenance tends to use only forecast results as a reference. The maintenance department usually decides which road segments to repair in the following year based on available data. Maintenance departments often make pavement maintenance decisions according to national norms and standards. In the decision-making process, many other influencing factors are neglected, in addition to the analysis of the pavement condition indicators. This has also resulted in annual maintenance and a failure to meet expectations.

Following the development of road maintenance technology, many mature pavement performance evaluation methods have been developed, including the regression model method [4], systematic analysis evaluation method, attribute theory method, and neural network algorithms [5]. The regression model method uses a large amount of measurement data to establish corresponding mathematical models that represent different types. However, it is difficult to express accurately the complex relationship between subjective and objective pavement evaluations. The correlation between the evaluation results and measured data was unsatisfactory and restricted by geographical conditions. The analytic hierarchy process and fuzzy synthetic evaluation methods are the main methods used for systematic analysis and evaluation because they are clear and theoretical. Expert survey scores are also used in pavement evaluations; however, their drawbacks include the presence of excessive artificial factors. However, these two methods are not highly pertinent, and it is difficult to evaluate objectively and fairly the pavement conditions. Attribute theory and neural network algorithm methods are similar to the grey method. However, there were some differences among the three groups. Calculation using the attribute method is tedious. The neural network method is difficult to model because of the slow convergence speed of the BP network and the tendency toward local convergence. Gray's theory not only synthesises the advantages of these methods but also avoids their disadvantages and achieves good results in pavement maintenance management. In 1982, Professor Deng Julong proposed the theory of grey systems [6]. This theory has been used to study uncertainty problems with limited data. It extracts valuable information, primarily by generating and developing partially known information. In addition, we realised the correct description and effective monitoring of the system operation behaviour and evolution law. The basic idea of this theory is that, regardless of the complexity of the target system, it is still interconnected and orderly with global functions and data as a behavioural characteristic of the system, always implying a certain regularity. The grey theory is suitable for the establishment of pavement maintenance decision models owing to the aforementioned advantages.

Currently, numerous methods are available for pavement maintenance assessment. Feng used the hierarchical cluster method to group road sections with the same traffic conditions, road surface structure, construction quality during the construction period, road environment, and degree of road surface microscopic damage into the same road type. They selected road sections that met the maintenance conditions to reduce maintenance costs [7]. Wei adopted a multi-attribute comprehensive analysis method to make decisions on asphalt pavement maintenance measures. First, the basic attributes of each maintenance measure were analysed in detail. Six basic attributes, namely, the service life of asphalt pavement, maximum gap difference before and after maintenance of asphalt pavement, degree of construction difficulty of maintenance technology, maintenance cost, influence degree of maintenance on traffic, and aesthetic appearance of road surface after maintenance, were selected as evaluation indices for decision-making [8]. However, most evaluation, prediction, and decision-making methods or models are based on regression analysis, which is inapplicable and lacks accuracy for practical applications. However, the pavement performance and external environment are constantly changing; therefore, it is not scientific to use constant indicators and weights in the evaluation process.

Grey relational analysis (GRA) is associated with a broad range of applications across various industries, and many scholars use it for similarity calculations and ranking. For example, Chen et al. utilised an improved entropy-based GRA to identify and rank critical causal factors in aviation accidents [9]. Based on the results of GRA, Zhang et al. emphasised the prioritisation of wall thickness as the most crucial structural factor in diesel particulate filter design [10]. Wang et al. employed GRA to calculate financial trading strategies and make market timing decisions [11]. The GRA method also has applications in pavement maintenance. Guo Rui analysed the grey entropy correlation coefficients of pairs factors influencing rut deformation and mixture dynamic stability based on grey entropy theory [12]. Yu Jiangmiao proposed and demonstrated an evaluation method for asphalt pavement micro-surface treatments based on grey system modelling and the grey relational degree theory. This method can be successfully applied with or without other pavement maintenance treatments [13]. Yuji et al. proposed an improved grey prediction model that obtained the prediction interval of maintenance service time and used it as the basis for active maintenance service decision-making [14].

Currently, numerous research studies exist on the cost-effectiveness analyses of pavement maintenance using materials. Many researchers have sought to improve maintenance quality and reduce costs by investigating new materials [15]. Geçkil et al. examined the impact of steel fibre dosage on concrete pavement thickness and cost. Their study revealed that with an increase in the steel fibre dosage, the concrete pavement thickness decreased by 4.35 % to 18.66 %, while the pavement costs increased by 56.50 % to

74.07 % [16]. Moreover, these researchers explored the availability and cost-benefit relationship of concrete containing blast furnace slag in soils with lower bearing strengths for pavements. Their calculations determined that the addition of blast furnace slag reduced the concrete pavement thickness by 1.58-3.38 % and lowered costs by 5.59-10.30 % [17]. In addition, some scholars focussed on the prediction of pavement quality deterioration by studying pavement deformation that led to the development of numerous permanent deformation models for predicting rutting. Karadag et al. employed resonant column tests to assess the deformation characteristics of unbound granular materials, thus allowing them to predict the total permanent deformation occurring on pavements during specific load cycles. Subsequently, permanent deformation model equations were established for various pavement profiles using a curve-fitting approach [18]. Despite the extensive research on pavement maintenance costs, limited research has been conducted on pavement quality assessments.

Maintenance decisions are the most important basis of proactive maintenance strategies. In the field of maintenance decisions, popular traditional pavement performance decision methods mainly focus on how to use the monitored data of several key pavement condition indices. Moreover, most studies are concerned with maintenance costs rather than maintenance benefits [19]. There are some common methods in the field of qualitative analysis, but some of them do not apply to the scenario of this study, where the available data are limited, known information is rare, and the occurrence of failure is irregular. The Markov method has the limitation of being a non-after-effect prerequisite. The use of artificial neural networks and statistical methods is impossible without sufficient data. In contrast, the gray systems theory allows the construction of predictive models with small sample size and irregular data without any assumptions [20].

In this study, a decision optimisation model for asphalt road grades was established using the grey relational sorting method, and a cost-benefit analysis was conducted on the results of this model. The relationship between the desultorily limited and discrete highway detection data was investigated. By analysing the road surface condition data of some sections of the road, dynamic variables were introduced to calculate the weight of each variable and a comprehensive ranking was calculated. Subsequently, the priority order and optimal maintenance time of pavement maintenance were determined, and pavement maintenance decisions and maintenance plans were made.

2. Highway pavement maintenance decision influencing factors

Many factors affect the decision to maintain a pavement and the relationships between them are complex. These influencing factors mainly involve the design, construction, and operation, and most of these are uncertain. In general, pavement maintenance decisions need to consider pavement performance, road-structure characteristics, traffic volume, pavement age, climate, and other factors.

a) Road-structure material

In pavement maintenance sequencing, it is difficult to quantify the structural materials of the pavements. If the grading type of the pavement mixture and actual test parameters of the mixture can be used, the structural type of a specific pavement can be quantified. Based on the recent quantitative research on the surface characteristics of asphalt pavements on highways, the computational model can be expressed as follows [21]:

$$PMC = a_1 D_1 + a_2 D_2 + a_3 D_3 \tag{1}$$

$$PSME = 27{,}37 \cdot PSC^{0{,}645} \tag{2}$$

where a_1, a_2 and a_3 are the surface material coefficients of the surface, middle, and base courses, respectively; D_1, D_2 and D_3 are the thicknesses of the surface, middle, and base courses of the pavement, respectively; PMC is the pavement material coefficient, and PSME is the pavement structural material evaluation index.

b) Pavement age

Pavement age is another factor that influences pavement maintenance decisions. The starting time of the pavement age is the year of completion of new reconstruction or major and medium repairs. The condition of pavement damage and the bearing capacity of the pavement structure are closely related to the age of the road. As the age of the road increases, the bending value of the pavement increases and the overall stiffness decreases, leading to fatigue failure and gradual aging of the pavement material. In general, the older the road and the closer it is to its designed lifetime, the more important it is to undergo pavement maintenance [22].

c) Traffic volume

Vehicles are the primary service entities of expressways. Traffic volume is a direct cause of pavement fatigue damage. The vehicular load is the main cause of highway subgrade and pavement structural damage. Under the same conditions, as the traffic volume increases, the deterioration rate of the pavement increases. On expressways or high-grade highways, the traffic volume, which is referred to as the annual average daily traffic herein, is larger than that on a general highway, and the accumulative action of the standard axle load increases, thus leading to a faster decline in pavement performance. Therefore, the traffic volume must be considered in pavement maintenance decisions.

d) Pavement maintenance quality index (PQI)

A pavement maintenance quality index was used to evaluate the overall quality of the pavement. The PQI is expressed as follows [21],

$$\mathrm{PQI} = w_{PCI} PCI + w_{RQI} RQI + w_{RDI} RDI + w_{PBI} PBI + w_{SRI} SRI \tag{3}$$

where the function PCI is the pavement surface condition index, RQI is the pavement riding quality index, RDI is the pavement rutting depth index, PBI is the pavement bumping index, SRI is the pavement skidding resistance index; ω_{PCI}, ω_{RQI}, ω_{RDI}, ω_{PBI}, ω_{SRI} are the weights of the corresponding indices, respectively, and $\omega_{PCI} = 0.35$, $\omega_{RQI} = 0.30$, $\omega_{RDI} = 0.15$, $\omega_{PBI} = 0{,}10$ and $\omega_{SRI} = 0{,}10$.

e) Pavement structure strength index (PSSI)

The pavement structural strength was evaluated using the pavement structure strength index. PSSI is expressed by the following equation,

$$PSSI = \frac{100}{1 + a_0 \exp(a_1 SSI)} \tag{4}$$

$$SSI = \frac{l_d}{l_0} \tag{5}$$

where $a_0 = 15.71$, $a_1 = 5.19$, SSI is the structural strength index, l_d is the pavement design deflection (mm), and l_0 is the measured pavement deflection (mm).

f) Other influencing factors

In addition, many other factors, such as construction quality, pavement drainage, and maintenance levels, directly or indirectly affect the development of pavement performance. Nevertheless, these factors are indirectly reflected in the pavement performance. Analysing these factors individually is complex. In this study, these factors were not considered separately as influencing factors in pavement maintenance decisions. In summary, the road structure material, pavement age, traffic volume, *PQI*, and *PSSI* were the five factors selected as influencing factors.

3. Establishment of highway pavement decision optimisation model

The results were obtained based on the sorting method of pavement performance parameters. Usually, the more serious the pavement damage is, the more advanced the order is, and an increased need for priority maintenance exists [23]. However, this was not entirely consistent with the actual maintenance work. The joint action of the pavement age and traffic volume should be fully considered, particularly under conditions of limited maintenance funds. Policymakers should maximise our limited investments and not necessarily fix the worst roads first. In this study, highway sections were classified using the grey relation degree method, and the sections that required the most maintenance were obtained. subsequently, cost-benefit analysis was performed to determine the pavement maintenance time.

3.1. Grey relation analysis (GRA)

Grey relation analysis is a multifactor statistical analysis method. Based on the sample data for each factor, the intensity, size, and order of each factor were described by the degree of grey linkage [24]. The purpose of the GRA is to reveal the strength of the relationships between various factors. Finally, comparison sequences were sequenced according to the degree of correlation. The objective of a comprehensive evaluation can also be regarded as the index values corresponding to each evaluated object, and these index values often need to be sorted. The comparison sequence consisted of index values of the assessed objects [25–27].

In this study, the selected influencing factors were analysed using the grey relation method, and the original data were made dimensionless using range normalisation. After the degree of correlation was sorted, the correlation matrix was normalised, and the weight of each influencing factor was obtained. As the dimensions of each influencing factor were different, the influencing factor with large dimensions becomes the main or even the only influencing factor if the weight is directly multiplied by the influencing factor data. Therefore, the final score was calculated by multiplying the weights by non-dimensional matrices.

a) Research objective for GRA

The reference data column is the standard data column in the grey relation analysis method [28, 29] and is denoted as X0. Let the first indicator value be denoted as $X_0(1)$, the second indicator value as $X_0(2)$, and the kth indicator value as $X_0(k)$. Concisely, the following equation may be used,

$$X_0 = \{X_0(i)\} \quad i = 1, 2, 3 \ldots, n \tag{6}$$

b) Dimensionless

Generally, the original sequence of variables has different dimensions or orders of magnitude. To ensure the reliability of the analysis results, a non-dimensionalised sequence of variables was required.

After non-dimensionalisation, the sequence of each factor forms the following matrix,

$$(X_0, X_1, \cdots, X_n) = \begin{pmatrix} x_0(1) & x_1(1) & \cdots & x_n(1) \\ x_0(2) & x_1(2) & \cdots & x_n(2) \\ \vdots & \vdots & \vdots & \vdots \\ x_0(N) & x_1(N) & \cdots & x_n(N) \end{pmatrix}_{N\cdot(n+1)} \tag{7}$$

$$x_i(k) = \frac{x_i^{'}(k) - x_{i\min}^{'}}{x_{i\max}^{'} - x_{i\min}^{'}} \quad i = 1, 2, 3 \ldots, n;\ k = 1, 2, 3, \ldots, N \tag{8}$$

where $x_i^{'}(k)$ is the kth original data point of the ith index, and $x_{i\max}^{'}$ and $x_{i\min}^{'}$ are the maximum and minimum values of the ith index, respectively.

c) Difference sequence, maximum and minimum differences

The absolute difference between the first column (reference sequence) and the other columns (comparison sequence) in the corresponding period forms the following absolute difference matrix:

$$D_{oi}(k) = |x_0(k) - x_i(k)| \quad i = 1, 2, 3 \ldots, n;\ k = 1, 2, 3, \ldots, N \tag{9}$$

The maximum and minimum values in the absolute difference matrix represent maximum and minimum differences, respectively.

$$\max_{\substack{1\le i\le n\\1\le k\le N}}\left\{\Delta_{0i}(k)\right\}\overset{\Delta}{=}\Delta(\max) \tag{10}$$

$$\min_{\substack{1\le i\le n\\1\le k\le N}}\left\{\Delta_{0i}(k)\right\}\overset{\Delta}{=}\Delta(\min) \tag{11}$$

d) Correlation coefficient

When the association degree of the reference and comparison data columns was analysed, the association degree of each indicator was first analysed, which was represented by the concept of the association coefficient. The equations used for calculations are,

$$\eta_i(k)=\frac{\Delta\min+\lambda\Delta\max}{\Delta_i(k)+\lambda\Delta\max} \tag{12}$$

$$\Delta_i(k) = |X_i(k) - X_0(k)| \tag{13}$$

$$\Delta_i(k) = |X_i(k) - X_0(k)| \tag{14}$$

$$\Delta\min = \min_i\min_k |X_i(k) - X_0(k)| \tag{15}$$

$$\Delta\max = \max_i\max_k |X_i(k) - X_0(k)| \tag{16}$$

where $\eta_i(k)$ is the correlation coefficient of index K between X_i and X_0, and λ is the resolution coefficient (usually ranging between zero and one). In this study, $\lambda = 0.5$.

e) Computational association order

For each evaluation object (comparison sequence), the mean values of the correlation coefficients of each indicator and the corresponding elements of the reference sequence were calculated to reflect the correlation relationship between each evaluation object and the reference sequence, which is called the correlation sequence, and is denoted as

$$r_{ki}=\frac{1}{n}\sum_{k=1}^{n}\alpha_k\eta_i(k) \tag{17}$$

Each indicator plays a different role in the comprehensive evaluation, and the weighted average value of the correlation coefficient can be calculated as follows,

$$r_{ki}^{'}=\frac{1}{m}\sum_{k=1}^{m}W_k\eta_i(k) \qquad k = 1, 2, ..., m \tag{18}$$

3.2. Improvement of grey relation sorting

In general, when conducting grey correlation analysis, the entropy weight method and analytic hierarchy process are used to assign weights to each index according to the original data. There were too many artificial factors in the results calculated using these methods, which were quite different from the actual situation. In this study, the correlation order data obtained by the gray correlation analysis were used to normalise the index weight. The close relationship between the indicators reflects the importance of each indicator, and the calculated weight is more consistent with the actual situation.

a) Calculating weight

Normalised according to the obtained correlation order, the weight of each indicator was obtained as follows,

$$w_i=\frac{r_{ki}^{'}}{\sum_{k=1}^{N}r_{ki}^{'}} \qquad i = 1, 2, ..., n;\ k = 1, 2, ..., m \tag{19}$$

where the weight $W = [w_0, w_1, ...w_n]$ for each index.

b) Object score evaluation

According to the weight *W* and the non-dimensionalised matrix obtained in the second step, the score of each evaluation object was obtained by multiplication, as shown in *Equation 20*. The object scores were then sorted.

$$Y=X^{*}W^{T}=\begin{pmatrix}x_0(1) & x_1(1) & \cdots & x_n(1)\\ x_0(2) & x_1(2) & \cdots & x_n(2)\\ \vdots & \vdots & \vdots & \vdots\\ x_0(N) & x_1(N) & \cdots & x_n(N)\end{pmatrix}_{N\times(n+1)}\begin{bmatrix}w_0\\ w_1\\ \vdots\\ w_n\end{bmatrix} \tag{20}$$

3.3. Cost-benefit analysis

After the maintenance priority of each road section was analysed, the road section with the highest priority was analysed further, and the optimal maintenance time for the target road section was obtained. When the time of pavement maintenance is determined by the cost-benefit evaluation method, the maintenance benefit is expressed as the area enclosed by the pavement performance curve. The area enclosed by the pavement performance decay curve and up-and-down benefit baseline is called the exponential benefit zone. After the maintenance measures are adopted, the increment in the benefit area is called the maintenance benefit area.

a) Lowest acceptable level of pavement performance index

The minimum acceptable performance indicators for maintenance measures were the limits for the pavement condition performance indicators in the calculation of the area of benefit. The minimum acceptable level was divided into upper and lower limits according to the decay trends of the pavement performance indices. When the pavement performance index decreases with the age of the vehicle, the minimum acceptable level is the lower limit. The minimum acceptable level is the upper limit at which the pavement performance index increases with age. Any part of the benefit calculation that exceeds the minimum acceptable performance indicator is not considered beneficial. In this project, the pavement damage indices *PCI* and *RDI* were used as benefit-calculation indices. Therefore, the minimum acceptable level was the floor value of the benefit calculation, that is, 80.

b) Calculation of the maintenance benefits

When conservation measures are adopted, the increase in the benefit area is called the conservation benefit area. The area S, shown in Figures 1 and 2 is the pavement use benefit.

The comprehensive maintenance benefit was calculated using Equation(21).

$$S = K_1 S_{PCI} + K_2 S_{RDI} \tag{21}$$

where $K_1 = 0{,}6$ i $K_2 = 0{,}4$.

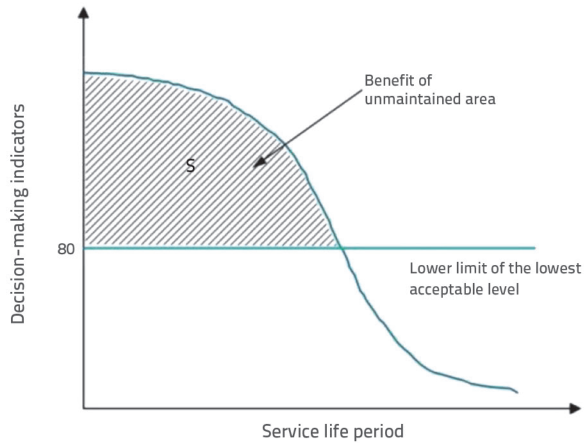

Figure 1. Benefit of unmaintained area

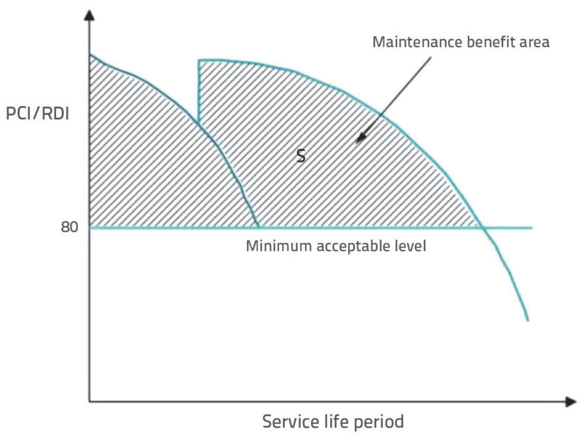

Figure 2. Maintenance benefit area

c) Determination of the maintenance time

Pavement maintenance costs include the present value of the pavement maintenance costs and the residual value of roads. The present value of the cost includes the costs to the owner and user. The present cost value was calculated using Equation (22).

$$PWC = \frac{C}{(1+i)^n} \tag{22}$$

where *PWC* is the present value of the costs and expenses, *C* is the cost, *i* is the discount rate, and *n* is the computation period.

The residual value of the pavement is the proportion of the remaining life in its service life, and the residual value of the pavement is calculated according to Equation (23):

$$SV = (1 - \frac{L_A}{L_E})C_r \tag{23}$$

gdje L_A predstavlja vrijeme od posljednje godine održavanja do where L_A represents the time from the last maintenance year to the end of the life cycle, L_E is the service life of the maintenance measures, and C_r is the cost of the conservation measures.

The maintenance cost refers to the direct cost of pavement maintenance and consists of the material and labour costs required to implement maintenance measures. According to the cost-benefit ratio of different conservation schemes, the conservation timing scheme with the largest cost-benefit ratio was determined as the best conservation timing.

4. Model application

In actual pavement maintenance, pavements with structural damage are prioritised for maintenance and repair. To properly use maintenance funds and improve the best utilisation rate of the road surface, the gray relational degree method was used to rank the maintenance priority of the pavement.

Data from highway sections were used for analysis. The original data are listed in Table 1. Suppose that {Pavement Age, Traffic Volume, *PQI*, *PSME*, *RSSI*} = X_i. Because the original data sequence has different dimensions, it must be non-dimensionalised.

It can be observed from the table that as the pavement quality worsens, the pavement evaluation index decreases. This index should be considered before making pavement evaluation decisions. The specific process was set to 100, the maximum value of *PQI*, *PSME,* and *PSSI*; subsequently, the value of 100 minus these the sum of the three items was used before non-dimensionalisation. This was because less extensive

Table 1. Raw data of various influencing factors in different road sections

Road	Pavement age [year]	Traffic volume	Pavement maintenance quality index (PQI)	Pavement structural material evaluation index (PSME)	Pavement structure strength index (PSSI)
A	12	7541	81.90	80.48	95.15
B	14	7456	80.10	76.18	91.45
C	15	12423	73.80	66.29	89.69
D	8	4536	84.60	78.55	97.02
E	13	5351	82.35	68.02	94.34

Table 2. Incidence matrix

Incidence matrix	X_1	X_2	X_3	X_4	X_5
X1	1.00	0.6670	0.6547	0.6092	0.7434
X2	0.7003	1.00	0.8854	0.6859	0.7699
X3	0.6681	0.8716	1.00	0.6726	0.8318
X4	0.6516	0.6859	0.6974	1.00	0.6464
X5	0.7192	0.7123	0.8055	0.5693	1.00

Table 3. Ranks of final scores

Ranking	Road	Pavement age [year]	Traffic volume	*PQI*	*PSME*	*PSSI*	Final score
1	C	15	12.423	73.80	66.29	89.69	1.000
2	B	14	7.456	80.10	76.18	91.45	0.543
3	E	13	5.351	82.35	68.02	79.34	0.441
4	A	12	7.541	81.90	80.48	95.15	0.294
5	D	8	4.536	84.60	78.55	97.02	0.025

maintenance was required when the values of *PQI*, *PSME*, and *PSSI* increased. If non-dimensionalisation was conducted directly, the result would prioritise the maintenance of the pavement with high values of these three indices.
The result of the non-dimensionalisation of the original data is X^*.

$$X^* = \begin{bmatrix} 0.57 & 0.38 & 0.25 & 0.00 & 0.26 \\ 0.86 & 0.37 & 0.42 & 0.30 & 0.76 \\ 1.00 & 1.00 & 1.00 & 1.00 & 1.00 \\ 0.00 & 0.00 & 0.00 & 0.14 & 0.00 \\ 0.71 & 0.10 & 0.21 & 0.88 & 0.37 \end{bmatrix} \quad (24)$$

The association matrix obtained after the data analysis is shown in Table 2.
After the calculation, the weight of each indicator was obtained as follows,

$$W = [0{,}194\ 0{,}205\ 0{,}210\ 0{,}184\ 0{,}207] \quad (25)$$

The final score was obtained by multiplying each influencing factor by its corresponding weight. The sorting results are listed in Table 3.
As shown in Table 3, after sorting by the gray correlation degree, the road with the highest score obtained the maintenance priority. It can be observed that route C should be prioritised for maintenance in study areas. It is suggested that although the pavement performance index still has a significant influence on decision-making, it is no longer a unique evaluation index. Pavement age and traffic volume also played a part role in the final score.
As noted above, Section C should be given maintenance priority, and the optimal maintenance time for Section C can be determined using a CBA. Based on the predictive model curve of Ma Weizhong [30], the attenuation model of preventive maintenance, medium maintenance, and overhaul was established by referring to the prediction model curve. The

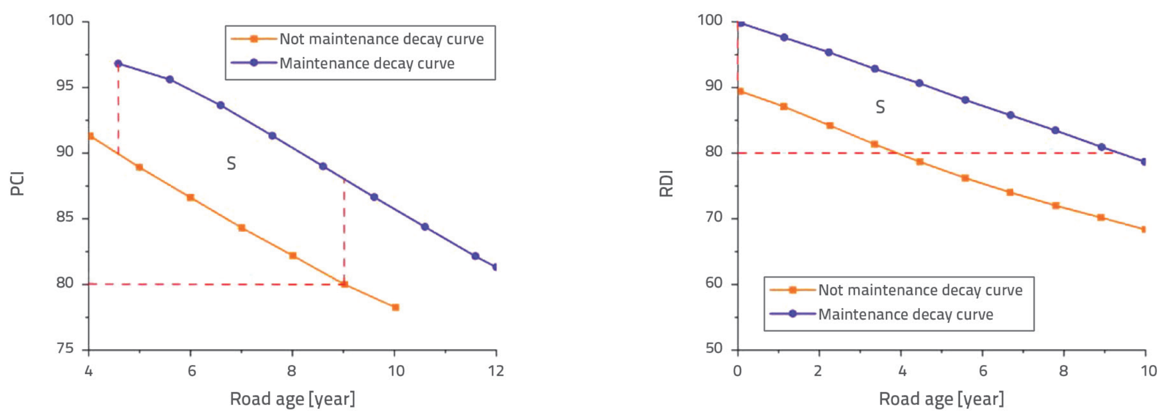

Figure 3. Schematic of benefit calculation for PCI and RDI preventive maintenance

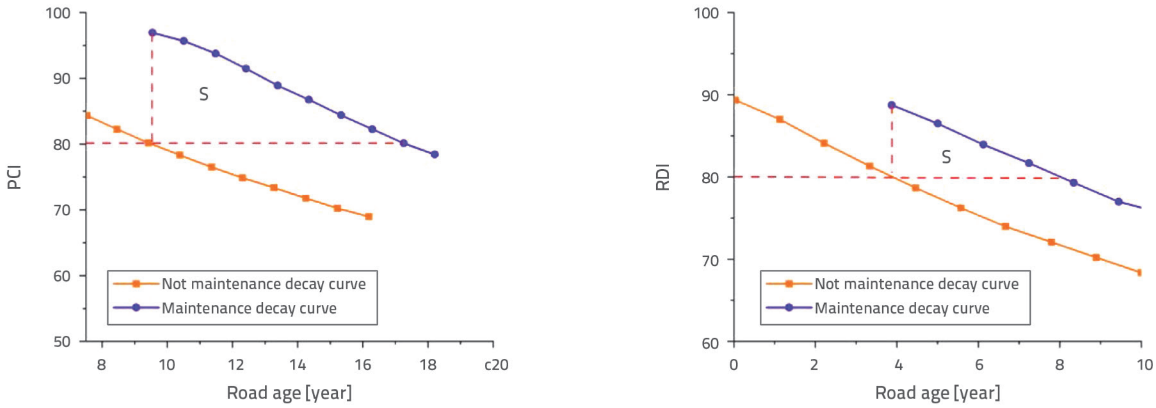

Figure 4. Schematic of calculation of maintenance benefit of PCI and RDI for large and medium repairs

Table 4. Calculation results of maintenance benefits

Nature of maintenance engineering	PCI Maintenance efficiency (S_{PCI})	RDI Maintenance efficiency (S_{RDI})	Comprehensive benefits S ($S = K_1S_{PCI} + K_2S_{RDI}$)
Preventive maintenance (S_1)	35.09	67.79	48.17
Medium repair (S_2)	71.73	7.51	46.04
Large repair (S_3)	71.73	7.51	46.04

Table 5. Cost-benefit ratio calculation results

Year	First year	Second year	Third year
Cost–benefit ratio	0.39	0.37	0.56

corresponding model curves are shown in Figures c and d. The S-shaped area of the enclosed regions in the figure refers to each maintenance benefit, and the S-shaped area is enclosed by a decay curve after maintenance. The PCI and RDI decay curves are not maintained; the lowest acceptable level is the index transition line before and after maintenance in the year of maintenance. The area of a region was calculated using the area integral of the curve. The calculation results for the dependency allowances in this section are listed in Table 4.

As shown in Figures a and b, the approximate maintenance cost (from the following year to the following three years) was inferred based on the road surface condition index of this section in recent years and the corresponding maintenance costs. In addition, the cost-effectiveness ratio of the maintenance measures in alternative years was calculated; that is, the maintenance unit could determine the maintenance cost according to the proposed maintenance measures. The calculation results are listed in Table 5. The cost-efficiency ratio of the selected road section adhered to the order of Second< First< Third. Therefore, the best time for conservation, determined by the cost-benefit analysis, was in the second year.

5. Conclusions

In this study, the detection data from a section of five expressways in Jiangsu Province, China, were selected as the object of analysis. Available pavement condition data were primarily used for pavement condition evaluation and maintenance time determination. The synergistic effects of these factors on the asphalt pavement performance were investigated by establishing an improved grey relation sorting and benefit-cost analysis model. In actual maintenance work, the pavement quality is often evaluated using fixed indicators and weights. Analysis of the evaluation results is also a priority for the maintenance of road surfaces with structural damage. To establish a more reasonable evaluation system and improve the best utilisation rate of the pavement, the section was analysed using the grey relation degree method. The results indicated that the higher the score, the higher the maintenance priority. The following conclusions were drawn from this study:

- The traffic volume, pavement age, and technical conditions of the pavement were chosen as the principal influencing factors. To reveal the strength of the relationship between various factors, a grey relation analysis was performed. The grey relation sorting method comprehensively considers the spatial influence of the whole factor index, especially when the sample size of the factor index is small and the data are discrete, which could avoid the single direction deviation to analyse comprehensively the mutual relationship between the indicators and reflect the influence of the entire factor index space. It was found that the ranking results obtained using this model were more consistent with the actual situation, and this model also provided a reasonable basis for decision-makers. In addition, the computational effort was significantly reduced.

- Pavement performance and the external environment are constantly changing. Therefore, it is not scientific to use constant indices and weights in the evaluation process. The advantage of the grey sorting model (which is based on grey relational analysis) is that indicators can be selected according to the actual situation, and weights can then be assigned based on the closeness of the relationships between indicators. The analysis results showed that the weight obtained using this method was more flexible and targeted road surfaces under different conditions.
- The optimal maintenance timing for expressway asphalt pavements was determined using the cost-benefit analysis method. This method was used to analyse the service performance predictive model for asphalt pavements and thus obtain the best maintenance time. Decision-makers can analyse the pre-maintenance pavement according to the best maintenance time and budget when making decisions and take certain maintenance measures in combination with various factors, such as budget limitations. This method provided a guiding function.

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