Optimization model for timing of preventive maintenance of asphalt pavement based on decision trees

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Abstract: The timing of preventive maintenance for asphalt pavement determines the effectiveness and cost-effectiveness of preventive maintenance measures. Firstly, a weighted average method combining subjective and objective factors is used to evaluate the performance index of road sections and select preventive maintenance measures. Secondly, a decision tree model for preventive maintenance of highways in Gansu Province is established using field measurement data to determine the timing of preventive maintenance for road sections. Finally, the model is validated using the example of the G22 Qingdao-Lanzhou Expressway by evaluating the pavement service performance index and the timing of preventive maintenance. The results show that compared to directly establishing decision trees based on uniform standards, the decision tree established using field measurement data reflects the differences in the importance of various decision indicators and respects the objectivity of road data. It improves the poor portability of the original decision tree model and enables more accurate determination of the timing of preventive maintenance.

Keywords: asphalt pavement, timing of preventive maintenance, decision tree, weighted average method.

1. Introduction

The timing of implementing preventive maintenance measures determines the effectiveness of pavement maintenance. Missing the appropriate maintenance timing can lead to serious pavement defects, rendering preventive maintenance measures ineffective and resulting in the wastage of resources such as personnel and funding. It can also increase maintenance costs. Therefore, determining the timing of preventive maintenance is a critical issue in pavement maintenance. In China, various research methods have been used to determine the timing of preventive maintenance, including methods based on pavement condition index (PCI) or time, decision trees, driving quality index, damage index method, cost-benefit evaluation method, ranking method, and life-cycle assessment method. Each of these methods has its advantages and disadvantages. For example, using the riding quality index (RQI) to set maintenance thresholds cannot reflect other pavement defects such as cracks and skid resistance, lacking comprehensiveness. Cost-benefit and life-cycle methods have high computational complexity and consider numerous factors, making them difficult to implement. On the other hand, the decision tree model takes into account the causes of pavement condition indicators, is intuitive, and has the advantage of targeted maintenance. Therefore, this paper selects the decision tree model for determining the timing of preventive maintenance.

Li Haigang [1] used the GM (1,1) model to predict the pavement technical performance indicators PCI, RQI, RDI (rutting depth index), and SRI (skid resistance index), and established a decision tree model for maintenance decisions based on these four technical indicators. Wang Jing [2] analyzed the climate, environment, and pavement diseases in the Hexi Corridor region of Gansu Province and established a decision tree for asphalt pavement maintenance strategies on highways in the Hexi Corridor region of Gansu Province, using PCI, RQI/RDI, and SRI as decision indicators. However, there is a lack of corresponding explanations regarding the selection of control thresholds for preventive maintenance indicators PCI and RQI values. Ji Hongyan [3] used data mining software SPSS Clementine to establish decision tree models for asphalt pavement performance classification and regression trees and applied them in asphalt pavement performance evaluation. Zhang Yuntao [4] proposed a decision tree model for preventive maintenance of asphalt pavement in Beijing based on the Pavement Structure Strength Index (PSSI) and PCI as judgment indicators, and CR (crack rate), RD (rutting depth), SFC (skid resistance performance index), and IRI (roughness index) as decision indicators. Zhang Jinxi [5] established a decision tree model for the relationship between pavement condition and maintenance measures, using PSSI, RD, PCI, CK (crack rate), and LR (patching rate) as decision indicators, and mentioned using ranking methods to solve network-level pavement maintenance decision problems. Zhao Shuai [6] used a dynamic weighted evaluation method combining subjective and objective factors to comprehensively evaluate the pavement quality index (PQI), which considers the differences in road conditions and the importance of various sub-indicators, and has good applicability. Han Fei [7] proposed a method to determine the timing of preventive maintenance for asphalt pavement in Gansu Province based on cumulative axle load counts. Li Hailian [8] established a multi-indicator decision tree for maintenance types based on PCI, RCI (roughness condition index)/RDCI (rutting depth condition index), PBI (pavement bouncing index)/SRI, and PWI (pavement wear index) as decision indicators. Wei [10] used cost-benefit analysis to calculate the optimal implementation time for each preventive maintenance measure and applied it to a decision tree.

Regarding the determination of timing for preventive maintenance using decision tree models, most domestic and foreign scholars focus on the selection of decision indicators, with few studies fully utilizing inspection data to establish decision trees for determining the timing of preventive maintenance for different road sections. There is also a lack of explanations regarding the threshold values for dividing decision indicators. In light of this, this paper optimizes the original decision tree model for determining the timing of preventive maintenance on road surfaces and uses the optimized model to determine the timing of preventive maintenance for asphalt pavement on highways in Gansu Province.

2. Optimization of decision trees and subjective-objective weighting model

2.1. Model for determining timing of preventive maintenance based on decision trees

The decision tree is a method of decision-making represented in a tree-like structure, which involves a process of making judgments by outputting classification results through a series of test questions. The decision tree consists of three parts: the root node, intermediate nodes, and leaf nodes. The decision process is essentially the process of dividing the original dataset into two or more subsets through test conditions and making the subsets as “pure” as possible through a series of divisions, where each divided dataset preferably belongs to the same category. The decision tree can be divided into two types: classification trees and regression trees. Discrete variables are commonly used in classification trees, with common algorithms being ID3 (information entropy algorithm) and C5.0 (information gain) algorithm. Continuous variables are used in regression trees, with CART algorithm being a common algorithm.

The preventive maintenance decision tree is established to solve the problem of preventive maintenance decision-making by using a decision tree. The final decision tree is constructed by dividing

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the leaf nodes into leaf nodes representing preventive maintenance and other types of maintenance, creating a classification tree. In this paper, the CART algorithm is used, and the Gini index is employed as the selection criterion for the feature to be classified. The principle is as follows:

Suppose the set of sample examples is $S=\{e_1, e_2, \ldots, e_N\}$, where N examples are divided into m classes, and the proportion of examples in the i-th class C_i is $p_i = \frac{|C_i|}{N}$ $(1 \leq i \leq m)$. The *Gini* index of set S is defined as:

$$Gini(S) = 1 - \sum_{i=1}^{m} p_i^2 \tag{1}$$

Assuming that the cut-off point T divides the sample set S into two subsets, S1 and S2, the Gini index of cut-off point T dividing S is defined as:

$$Gini(A, T, S) = \frac{|S_1|}{|S|} Gini(S_1) + \frac{|S_2|}{|S|} Gini(S_2) \tag{2}$$

The Gini gain of cut-off point T dividing set S is:

$$Gini(S, T, A) = Gini(S) - Gini(A, T, S) \tag{3}$$

Different examples have different values for attribute A. When the N examples are sorted in ascending order based on the values of attribute A, the cut-off point T can generate N-1 cut-off points in set S, denoted as T_1, T_2, ..., T_{N-1}. If the adjacent examples on both sides of a cut-off point belong to the same class, the cut-off point is referred to as a balanced cut-off point; otherwise, it is called an unbalanced cut-off point. When choosing information gain as the measurement criterion, the optimal cut-off point is a non-balanced cut-off point.

The N examples are divided into M (M≤N) groups based on the categorical attribute: F_1, F_2, ..., F_M, where each group belongs to the same category. The midpoint between adjacent groups is selected as a candidate cut-off point, resulting in M-1 candidate cut-off points. The optimal cut-off point T_A of attribute A is selected among the M-1 candidate cut-off points with the maximum Gini index. The optimal cut-off points for other attributes are then calculated, and the attribute corresponding to the cut-off point with the maximum Gini gain among all attributes is selected as the expansion attribute. When all samples in all nodes belong to the same category, the division process stops, and a decision tree is formed.

The CART algorithm selects the attribute with the highest Gini index as the sub-node for division. Due to the large computational complexity, software for data mining such as SPSS Modeler can be used to assist in modeling, and the decision tree can be pruned using post-pruning methods.

2.2. Subjective-objective weighting method

The performance evaluation indicators of asphalt pavement are divided into four categories: pavement condition index (PCI), riding quality index (RQI), rutting condition index (RDI), skid resistance index (SRI), and pavement structure strength index (PSSI). By summing these four indicators with certain weights, the pavement quality index (PQI) can be obtained. Therefore, this paper selects PCI, RQI, RDI, and SRI as decision indicators for determining the timing of preventive maintenance on asphalt pavements. Under the subjective-objective weighting method, PQI' is used as the evaluation index to determine the type of road sections.

Subjective weighting method is a method in which decision-makers subjectively determine the weights of each sub-indicator based on practical experience and expert guidance. Typical methods include expert scoring method, Delphi method, and Analytic Hierarchy Process (AHP). Objective weighting method, on the other hand, determines the weights based on the actual data of each sub-indicator but does not reflect the differences in importance among the sub-indicators. Examples of objective weighting methods include entropy weighting method and principal component analysis method. Since subjective weighting cannot respect the objective reality of the data, it needs to be combined with the reward-punishment function in the objective weighting method. The reward-punishment function is an objective weighting method, calculated as follows:

Calculating reward-punishment weight

$$\beta_i = \frac{1}{y_i \sum_{i=1}^{n} \frac{1}{y_i}} \tag{4}$$

where y_i is the evaluation value of each sub-indicator, and βi is the reward-punishment weight of each sub-indicator.

Considering the advantages and disadvantages of both subjective and objective weighting methods, they can be combined. The weights α_i of the subjective weighting method can be determined based on practical experience, and the weights βi of the objective weighting method can be calculated using formula (4). By combining the subjective and objective weighting methods, the weighted average weighting method is obtained as follows:

$$\omega_i = \lambda\alpha_i + (1-\lambda)\beta_i \tag{5}$$

where ω_i is the weight of each sub-indicator, and λ is the subjective weight ratio coefficient.

The method of obtaining the weights of sub-indicators based on formula (5) is the subjective-objective weighting method used in this paper.

2.3. Combination and optimization of models

In this paper, the comprehensive weights and evaluation indicators are calculated using the subjective-objective weighting method based on the actual detection data of road sections. The data set is classified based on the numerical values of the evaluation indicators. Then, using the classification results as type data sets and the technical performance index type as attribute data sets, the optimal cut-off points for each technical performance index are calculated. In this process, the attribute with the maximum information gain ratio is selected to generate a node and perform division. If all samples in a node belong to the same category, it becomes a leaf node. Finally, the decision tree is formed, and the threshold for preventive maintenance of road surfaces is determined, thereby determining the timing of preventive maintenance for road surfaces. The combined optimization process is shown in Figure 1.

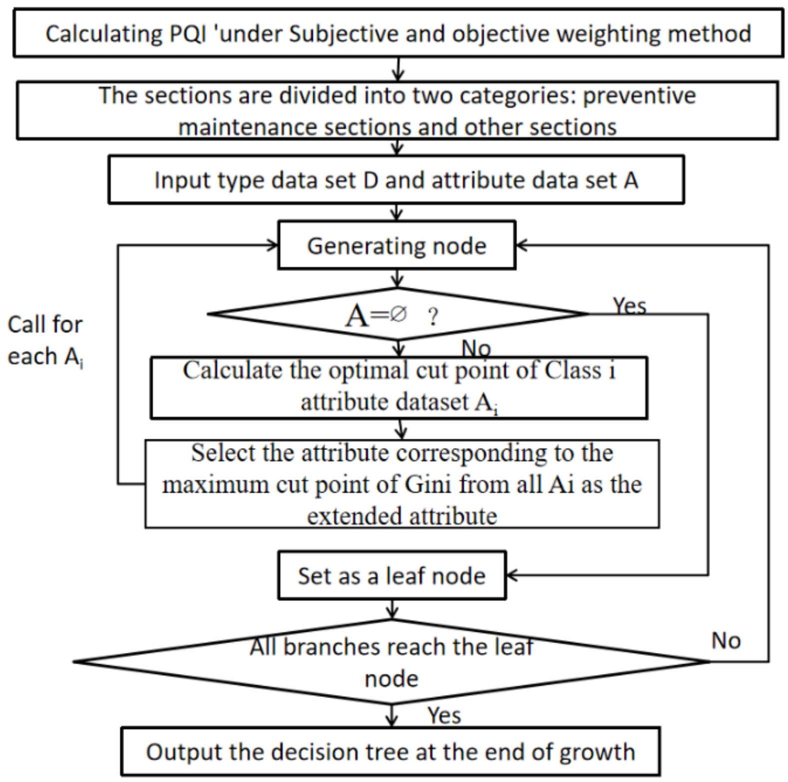

Figure 1. Flowchart of the combined optimization model.

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3. Case study

3.1. Project overview

Due to the typical and severe pavement diseases on G22 Qinglan Expressway and the fact that the environmental conditions of this highway section are representative of the Northwest region, which is in line with the climatic characteristics, this study selects the 2020 inspection data of the Pingliang section of G22 Qinglan Expressway as the basis for studying the decision-making of preventive maintenance for asphalt pavements in Gansu Province.

The length of this road section is 26.376 km, and each numbered road segment has a length of 1 km. The pavement condition and performance index detection data for certain road segments in 2020 are shown in Table 1.

Table 1. 2020 pavement condition detection data for road segments G22K1639-1658.

No.	Start Mileage	PCI	RQI	RDI	SRI
1	K1639+000	93.72	72.15	86.06	77.37
2	K1640+000	97.35	89.37	94.58	71.00
3	K1641+000	93.27	95.01	96.18	68.18
4	K1642+000	89.61	93.71	94.50	67.68
5	K1643+000	78.24	92.61	96.02	91.35
6	K1644+000	83.23	86.87	93.34	91.18
7	K1645+000	84.04	68.63	91.01	90.80
8	K1646+000	86.22	83.39	92.83	90.47
9	K1647+000	87.34	89.07	94.59	90.05
10	K1648+000	82.64	87.93	92.61	90.51
11	K1649+000	70.92	86.15	92.47	92.79
12	K1650+000	73.64	90.34	93.36	93.06
13	K1651+000	88.26	92.35	96.18	93.45
14	K1652+000	47.40	88.99	91.23	79.06
15	K1653+000	49.61	88.20	93.05	77.04
16	K1654+000	53.91	89.21	91.21	90.62
17	K1655+000	53.03	88.80	91.26	90.86
18	K1656+000	63.58	89.36	92.57	90.20
19	K1657+000	62.56	88.61	92.91	90.08
20	K1658+000	78.61	75.71	87.47	88.16

3.2. Performance evaluation of G22 qinglan expressway pavement

The weighting types for the comprehensive evaluation of multiple indicators can be categorized into subjective weighting and objective weighting. In actual maintenance, the subjective weighting method is commonly used to calculate the Pavement Quality Index (PQI) as an overall evaluation of pavement performance, as shown in formula (6).

$$PQI = \alpha_1 PCI + \alpha_2 RQI + \alpha_3 RDI + \alpha_4 SRI \tag{6}$$

In the formula, α_i represents the subjective weights of each sub-indicator. In the case of asphalt pavements on highways, the values are commonly set as 0.35, 0.40, 0.15, and 0.10 based on practical construction experience. However, in the actual pavement maintenance process, due to different

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environmental conditions, the PQI determined by subjective weights cannot serve as the basis for preventive maintenance of asphalt pavements in different regions. Therefore, objective weighting methods need to be combined. According to the objective weighting method, the data from columns 3 to 6 in Table 1 are processed using equations (1), (2), and (3) to calculate the technical performance sub-indicator reward and penalty weights, as shown in Table 2.

Table 2. Sub-indicator reward and penalty weights for G22 qinglan expressway segments.

No.	β_{PCI}	β_{RQI}	β_{RDI}	β_{SRI}
1	0.217	0.282	0.237	0.263
2	0.223	0.243	0.229	0.305
3	0.232	0.227	0.225	0.317
4	0.236	0.226	0.224	0.313
5	0.284	0.240	0.232	0.244
6	0.266	0.255	0.237	0.243
7	0.245	0.301	0.227	0.227
8	0.255	0.264	0.237	0.243
9	0.258	0.253	0.238	0.250
10	0.267	0.251	0.238	0.244
11	0.298	0.245	0.229	0.228
12	0.295	0.240	0.232	0.233
13	0.262	0.250	0.240	0.247
14	0.377	0.201	0.196	0.226
15	0.365	0.205	0.195	0.235
16	0.358	0.217	0.212	0.213
17	0.362	0.216	0.210	0.213
18	0.322	0.229	0.221	0.227
19	0.325	0.230	0.219	0.226
20	0.261	0.271	0.235	0.233

In equation (5), λ is the proportion coefficient of subjective weights, which depends on the service life of the pavement. For highways with shorter service life, λ has a smaller value, while for pavements with longer service life, λ has a larger value. In this study, λ is set as 0.5. By substituting λ=0.5 into equation (5), the dynamic weights for different road segments under the subjective-objective weighting method are shown in columns 2-5 of Table 3.

The subjective-objective weighting method is shown in Table 3.

$$PQI' = \omega_1 PCI + \omega_2 RQI + \omega_3 RDI + \omega_4 SRI \tag{7}$$

PQI' is the pavement usage performance index obtained by weighting the subjective and objective weights. Based on the unique geographical environment of high altitude and arid conditions in Gansu Province, a PQI' value of ≥85 is proposed as the criterion for setting preventive maintenance road segments for various small road sections of Gansu Province, as shown in Table 3.

Table 3. Calculation of dynamic weights for road segments and pavement performance index results.

Segment No.	ω_{PCI}	ω_{RQI}	ω_{RDI}	ω_{SRI}	PQI'	Preventive Maintenance
1	0.284	0.341	0.193	0.182	81.908	No
2	0.286	0.321	0.190	0.203	88.920	Yes
3	0.291	0.314	0.187	0.208	89.133	Yes
4	0.293	0.313	0.187	0.207	87.279	Yes
5	0.317	0.320	0.191	0.172	88.486	Yes
6	0.308	0.327	0.193	0.171	87.739	Yes
7	0.298	0.350	0.188	0.164	81.061	No
8	0.303	0.332	0.194	0.172	87.290	Yes
9	0.304	0.327	0.194	0.175	89.788	Yes
10	0.309	0.325	0.194	0.172	87.650	Yes
11	0.324	0.323	0.189	0.164	83.500	No
12	0.322	0.320	0.191	0.167	84.988	No
13	0.306	0.325	0.195	0.174	92.037	Yes
14	0.364	0.300	0.173	0.163	72.638	No
15	0.358	0.303	0.172	0.168	73.370	No
16	0.354	0.308	0.181	0.157	77.290	No
17	0.356	0.308	0.180	0.156	76.829	No
18	0.336	0.315	0.186	0.164	81.428	No
19	0.338	0.315	0.185	0.163	80.847	No
20	0.306	0.336	0.192	0.166	80.931	No
Mean	0.320	0.320	0.191	0.172	84.240	

3.3. *Establishment of preventive maintenance decision tree model*

First, the measured values of various technical performance indicators of the pavement are taken as input variables for the attribute dataset. Then, the road segments are divided into preventive maintenance segments and non-preventive maintenance segments, and the division results are taken as output variables. Taking the attribute data value PCI as an example, the category "1" represents preventive maintenance segments, while "2" represents other maintenance segments. The optimal cutoff points for PCI are calculated by sorting the PCI values in ascending order, as shown in Table 4.

Table 4. Ascending order table for PCI.

PCI	47.40	49.61	53.03	53.91	62.56	63.58	70.92
Category	2	2	2	2	2	2	2
PCI	73.64	78.24	78.61	82.64	83.23	84.04	86.22
Category	2	1	2	1	1	2	1
PCI	87.34	88.26	89.61	93.27	93.72	97.35	
Category	1	1	1	1	2	1	

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Based on Table 4, the 20 samples can be divided into 8 groups: F_1 = {47.40, 49.61, 53.03, 53.91, 62.56, 63.58, 70.92, 73.64}, F_2 = {78.24}, F_3 = {78.61}, F_4 = {82.64, 83.23}, F_5 = {84.04}, F_6 = {86.22, 87.34, 88.26, 89.61, 93.27}, F_7 = {93.72}, F_8 = {97.35}. The midpoints between every two adjacent groups are selected as candidate cutoff points, resulting in 7 candidate cutoff points for PCI: T_1=75.940, T_2=78.425, T_3=80.625, T_4=83.635, T_5=85.130, T_6=93.495, T_7=95.535.

Taking the cutoff point T_1 as an example, T_1=75.94 divides the sample set S into two subsets: $S_1=F_1$ and $S_2=S-S_1$. Then, $Gini(S)=0.5$, $Gini(S_1)=1-[(\frac{8}{8})^2+(\frac{0}{8})^2]=0$, and $Gini(S_2)=1-[(\frac{3}{12})^2+(\frac{9}{12})^2]=0.375$. Therefore, the Gini gain of using cutoff point T1 to divide the sample set S is calculated as follows:

Gini ($S, T1, A$) =Gini(S)-Gini ($A, T1, S$) $=0.5-(\frac{8}{20}\times 0+\frac{12}{20}\times 0.375)=0.275$. Similarly, the Gini gains for the remaining 6 cutoff points of PCI are calculated as 0.193, 0.250, 0.125, 0.184, 0.0054, and 0.037.

The maximum Gini gain for PCI is 0.275, corresponding to the cutoff point T_1=75.94. Therefore, the optimal cutoff point for PCI is T_{A1}=75.94. Based on Table 1, it can be observed that the decision tree division results are only related to the attributes PCI, RQI, and RDI, and not related to SRI. Therefore, it is only necessary to calculate the optimal cutoff points and Gini gains for PCI, RQI, and SRI. Similarly, the optimal cutoff points for RQI and RDI can be calculated, as shown in Table 5.

Table 5. Calculation of optimal cutoff points and gini gains.

PCI		RQI		RDI	
Cutoff Point	Gain	Cutoff Point	Gain	Cutoff Point	Gain
75.940	0.275	79.550	0.076	92.590	0.275
78.425	0.193	84.770	0.025	92.870	0.130
80.625	0.250	86.510	0.047	93.195	0.246
83.635	0.125	88.065	0.005	93.350	0.184
85.130	0.184	89.030	0.082	93.930	0.264
93.495	0.005	89.140	0.087		
95.535	0.037	89.365	0.131		
		89.855	0.087		
		91.345	0.156		

From Table 5, it can be seen that the maximum Gini gains for the performance indicators PCI, RQI, and RDI are 0.275, 0.156, and 0.275, respectively, corresponding to the optimal cutoff points 75.940, 91.345, and 92.590. Arranging the Gini gains in descending order, the extended attributes corresponding to them are PCI, RDI, RQI. In the figure, “1” represents preventive maintenance, and “2” represents other maintenance. Thus, a five-layer decision tree is formed, as shown in Figure 2.

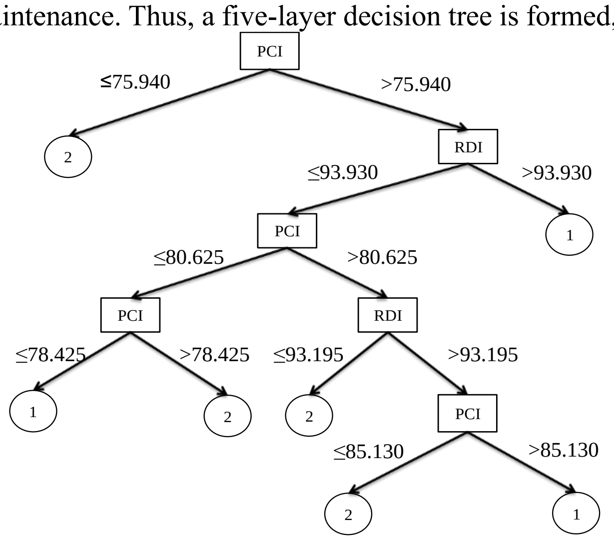

Figure 2. Decision tree for preventive maintenance.

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From Figure 2, it can be observed that the decision tree has a total of 7 leaf nodes, corresponding to 7 classification rules as follows:

(1) If PCI ≤ 75.940, adopt other maintenance measures.

(2) If PCI > 75.940 and RDI > 93.930, adopt preventive maintenance.

(3) If 75.940 < PCI ≤ 78.425 and RDI ≤ 93.930, adopt preventive maintenance measures.

(4) If 78.425 < PCI ≤ 80.625 and RDI ≤ 93.930, adopt other maintenance measures.

(5) If PCI > 80.625 and RDI ≤ 93.195, adopt other maintenance measures.

(6) If 80.625 < PCI ≤ 85.130 and 93.195 < RDI ≤ 93.930, adopt other maintenance measures.

(7) If PCI > 85.130 and 93.195 < RDI ≤ 93.930, adopt preventive maintenance measures.

In summary, rules (2), (3), and (7) are the rules generated by the decision tree for adopting preventive maintenance measures, indicating the timing for preventive maintenance of the road segment.

4. Conclusion

(1) In this paper, the overall evaluation of pavement performance is conducted by calculating PQI' using the subjective and objective weighting method. The road segments with PQI' ≥ 85 are selected as preventive maintenance segments. The results show that compared to the traditional PQI for overall evaluation of pavement performance, PQI' calculated using the subjective and objective weighting method gives more respect to the objective nature of the data.

(2) By combining and optimizing the subjective and objective weighting method with the decision tree model, this paper proposes a decision tree model for determining the timing of preventive maintenance for asphalt pavement on highways. This optimized model, compared to previous decision tree models, not only reflects the differences in the importance of various sub-indicators but also respects the objective nature of the data. The method has strong portability and can be used to determine the timing of preventive maintenance for different types of pavements, thereby improving the poor portability issue of the original decision tree.

(3) Through the optimized decision tree model, this paper identifies that the timing of preventive maintenance for the asphalt pavement on G22 highway is only related to the performance indicators PCI and RDI, while it is unrelated to the indicators RQI and SRI. The final determined maintenance timing is as follows: when the actual pavement technical performance indicators PCI and RDI fall within the following ranges: PCI > 75.940 and RDI > 93.930; 75.940 < PCI ≤ 78.425 and RDI ≤ 93.930; PCI > 85.130 and 93.195 < RDI ≤ 93.930. In these three cases, preventive maintenance is required; otherwise, other maintenance measures will be adopted.

(4) The optimized model used in this paper can not only use PCI, RQI, RDI, and SRI as decision indicators but also accommodate other decision indicators for calculating the timing of maintenance. Furthermore, the model can be applied not only to the maintenance decision-making of multiple segments on a single road but also to the determination of preventive maintenance timing for network-level pavements (multiple roads).

(5) In this paper, a dataset of 20 samples is used to establish the decision tree model. The more data available, the more scientifically accurate the construction of the decision tree will be. In future research, more precise determination of the timing of preventive maintenance can be achieved by utilizing a larger dataset of road segment data.

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