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Preventive Maintenance Decision-Making Optimization Method for Airport Runway Composite Pavements

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Abstract: Long-term preventive maintenance planning using finite annual budgets is vital for maintaining the service performance of airport runway composite pavements. Using the pavement condition index (*PCI*) to quantify composite pavement performance, this study investigated the *PCI* deterioration tendencies of middle runways, terminal runways, and taxiways and developed prediction models related to structural thickness and air traffic. Performance jump (*PJ*) and deterioration rate reduction (*DRR*) were used to measure maintenance benefits. Based on 112 composite pavement sections in the Long-term Pavement Performance Program, this study analyzed the influences of five typical preventive maintenance technologies on *PJ*, *DRR*, and *PCI* deterioration rates. The logarithmic regression relationship between *PJ* and *PCI* was obtained. For sections treated with crack sealing and crack filling, the *DRR* was nearly 0. For sections treated with fog seal, thin HMA overlay, and hot-mix recycled AC, the *DRR* was 0.2, 0.7, and 0.8, respectively. To solve the multi-objective maintenance problem, this study proposed a decision-making optimization method based on dynamic programming, and the solution algorithm was optimized, which was applied in a five-year maintenance plan. Considering different *PCI* deterioration tendencies of airport regions, as well as *PJ*, *DRR*, and costs of maintenance technologies, the preventive maintenance decision-making optimization method meets performance and financial requirements sufficiently.

Keywords: composite pavement; performance prediction model; preventive maintenance; decision-making optimization method; dynamic programming

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Citation: Ling, J.; Wang, Z.; Liu, S.; Tian, Y. Preventive Maintenance Decision-Making Optimization Method for Airport Runway Composite Pavements. *Appl. Sci.* **2024**, *14*, 3850. https://doi.org/10.3390/app14093850

Academic Editor: Raffaele Zinno

Received: 2 April 2024
Revised: 28 April 2024
Accepted: 28 April 2024
Published: 30 April 2024

1. Introduction

Concrete pavements are the main structure type for airport runways; however, with the approach to their designed service life and the rapid increase in air traffic volumes, the runway pavement performance deteriorates. Composite pavements are a special pavement structure type used for runway rehabilitation, where a hot mix asphalt (HMA) concrete overlay is paved onto the initial surface layer of the Portland cement concrete (PCC) pavement. Composite pavements have been widely adopted in airport runways constructed since the 1990s [1]. However, due to the modulus difference between PCC and HMA, composite pavements exhibit different distress features from both concrete pavements and asphalt pavements [2,3]. Thus, the timely and pertinent preventive maintenance of runway composite pavements is vital for improving the current performance or decelerating the performance deterioration rate so as to delay the demand for the next major repair or rehabilitation. Because of limited maintenance funds, it is necessary to make long-term preventive maintenance decisions that are economical and efficient. Long-term preventive maintenance aims to recover the surface performance before sharp deterioration occurs, which can contribute to the minimization of the total maintenance costs [4,5]. This maintenance strategy combines several maintenance methods to suit various annual maintenance funds. An effective long-term preventive maintenance strategy includes determining the runway region to be maintained, selecting the optimal maintenance time [6,7], and deciding the optimal maintenance method [8,9].

Accurate performance prediction for composite pavements is the prerequisite for conducting maintenance decisions [10]. Many scholars have developed prediction models to quantify the tendency for performance deterioration. Khattak et al. [11] developed distress prediction models for composite pavements in Louisiana based on the fundamental concept of pavement rate of deterioration as a function of age, which provided good prediction capabilities for assessing pavement deterioration. Kaya et al. [12] developed performance prediction models for composite pavements in Iowa based on statistics and artificial intelligence (AI) techniques, and the prediction accuracy was validated at the project and network level. Pandya et al. [13] predict the performance of eight long-term pavement performance (LTPP) composite pavement sections using layer thickness, material properties, traffic volumes, climatic data, and national calibration prediction models. Nur et al. [3] developed transverse cracking and longitudinal cracking performance prediction models for overlay treatment of composite pavements in Louisiana, considering the influence factors that included equivalent single axle load (*ESAL*), thickness of composite pavement structural layers, temperature indexes, etc. These researches focus on predicting the performance of road or highway composite pavements and show feasibility in these fields, while few prediction methods have been conducted on airport runway composite pavements, which present different structural and traffic conditions.

After predicting the pavement performance tendency, suitable preventive maintenance at a proper time is needed to prevent pavement performance from sharp deterioration. The linear programming method aiming to minimize total costs was first used to conduct pavement maintenance decision-making [14]. With the objective of minimizing the total maintenance cost while meeting the demand of pavement performance threshold, the mixed-integer programming model was also developed [15]. Yoon et al. [16] proposed a decision-making process to select appropriate maintenance treatments for reflective cracking in composite pavements. Selecting the optimal maintenance method and the optimal time is actually a multi-objective optimization problem, which aims to acquire the greatest improvement in pavement condition using as few maintenance funds as possible [17–19]. Compared to the linear optimization method, which maximizes maintenance benefits with limited costs, the multi-objective optimization method can both maximize maintenance benefits and minimize costs [20]. Meneses et al. [21] developed and implemented a multi-objective decision-aid tool that considers the minimization of costs and maximization of the residual value of pavements. Long-term preventive maintenance for multiple pavements is an even more complicated multi-objective optimization problem, which requires a multi-year maintenance plan and a combination of various maintenance strategies that consider the total maintenance benefits and costs for all pavements [22,23]. Roh et al. [24] proposed an airport pavement maintenance decision-making strategy based on multi-facility and multi-year network optimization models and analyzed the effect of initial budget, maintenance methods, costs, and thresholds on decision outcomes. To solve the multi-objective optimization problem of multi-pavement and multi-year maintenance, the dynamic programming (DP) method has drawn many scholars' interests [25]. Yoo et al. [26] proposed a hybrid DP procedure to determine the most cost-effective maintenance and rehabilitation activities for each section in a highway pavement network. Kuhn [27] used the approximate DP method to reduce the complexity of maintenance optimization problems. Mao et al. [28] developed a multi-stage DP model to achieve an optimal pavement maintenance strategy in a 30-year life cycle. Albatayneh et al. [29] developed an optimization algorithm based on DP to select the optimal treatment maintenance for road networks.

Despite plentiful studies on pavement maintenance planning, to the best of the authors' knowledge, few studies have been conducted on composite pavements due to a lack of performance deterioration and maintenance improvement data. This study first aimed to predict the pavement performance deterioration tendencies of different regions in airport runways with composite pavements. Then, this study investigated the benefits of typical preventive maintenance technologies according to data from the Long-term Pavement Performance (LTPP) program. Finally, a decision-making optimization method based on DP for long-term preventive maintenance was proposed, applied, and verified in a five-year maintenance plan.

2. Methods

2.1. Composite Pavement Performance Prediction

The occurrence times and deterioration rates of different pavement diseases vary because of such influences as pavement structure, climate, and traffic. The pavement condition index (*PCI*) was proposed to quantify the comprehensive surface performance of pavements [30]. The *PCI* can be used as an auxiliary decision-making indicator of long-term preventive maintenance. Sun et al. [31] proposed the following *PCI* predictive model for asphalt pavements:

$$PCI = PCI_0[1 - e^{-(\frac{\alpha}{y})^{\beta}}] \tag{1}$$

$$\alpha = \lambda[1 - e^{-(\frac{\eta}{l_0})^{\zeta}}] \tag{2}$$

$$\lambda = a_1 h^{b1} ESAL^{c1} \tag{3}$$

$$\eta = a_2 h^{b2} ESAL^{c2} \tag{4}$$

$$\zeta = a_3 h^{b3} ESAL^{c3} \tag{5}$$

$$\beta = a_4 h^{b4} ESAL^{c4} l_0^d \tag{6}$$

where PCI_0 is the initial *PCI*, which is usually 100 when construction or rehabilitation is completed; y is the pavement age; α is the pavement service life factor; β is the deterioration curve shape factor; l_0 is the initial pavement deflection (0.01 mm); h is the thickness of the asphalt layer (cm); *ESAL* is the daily equivalent single axle loading repetitions based on the B737-800 aircraft (/day); and a_n, b_n, c_n (n is 1, 2, 3, 4) and d are the regression coefficients.

The structures of asphalt pavement and composite pavement differ, as do their deterioration curves. This article replaces h in Equations (3)–(6) with h_e, which can be calculated as follows [32]:

$$h_e = (0.4C_F h_F + C_R h_R)/F \tag{7}$$

where h_e is the equivalent thickness of composite pavement (cm); C_F is the thickness discount coefficient of asphalt concrete (AC) overlay; h_F is the thickness of AC overlay (cm); C_R is the thickness discount coefficient of portland cement concrete (PCC) pavement; h_R is the thickness of PCC pavement (cm); and F is the crack control coefficient of PCC pavement. F is calculated as follows [33]:

$$F = (0.08534\frac{n_s}{100} - 0.3594k_0 + 106.2946)/100 \tag{8}$$

where n_s is the annual sorties of aircraft with take-off speeds faster than 140 knots (/year), and k_0 is the modulus of subgrade reaction (MN/m^3).

2.2. Preventive Maintenance Benefit Analysis

2.2.1. Performance Jump

This study used performance jump (*PJ*) as the measure of short-term maintenance effectiveness, which is an "immediate improvement" [34–36]. *PJ* is associated with the initial performance of pavement before maintenance [37,38]. Labi et al. [37] used a logarithmic model to describe the relationship between *PJ* and the initial performance condition. This study used the following logarithmic regression model to predict *PJ*:

$$PJ = a \times \ln(PCI_b) + b \tag{9}$$

where PCI_b is the *PCI* before maintenance, and *a* and *b* are the regression coefficients.

In this study, relationships between *PJ* and PCI_b were analyzed for composite pavements treated with five typical maintenance methods, namely crack sealing, crack filling, fog seal, thin HMA overlay, and hot-mix recycled AC. This study selected 112 sections of composite pavements from the LTPP program, comprising 33 sections treated with crack sealing, 28 with crack filling, 21 with fog seal, 19 with thin HMA overlay, and 11 with hot-mix recycled AC. The *PCI* of the selected sections was calculated according to the performance data in the LTPP database, where *PJ* was the difference between PCI_a (immediately after maintenance) and PCI_b (immediately before maintenance).

2.2.2. Deterioration Rate Reduction

Deterioration rate reduction (*DRR*) is used to describe the "slowing down" of pavement performance deterioration caused by maintenance [38,39]. The deterioration rate of *PCI* during the service years and *DRR* was calculated according to the performance data of the 112 composite pavement sections.

2.3. Long-Term Maintenance Decision-Making Optimization Method

This study aimed to propose a decision-making optimization method for long-term preventive maintenance based on DP. The application of DP in multi-objective decision-making optimization problems requires certain parameters, including stage variables, state variables, decision variables, state transfer equations, objective functions, basic equations, and constraints.

2.3.1. Stage Variable

The maintenance cost of composite pavements in airports is not supposed to exceed the limit of the annual maintenance budget. Thus, an optimization model based on DP should divide the maintenance period into several stages at intervals of 1 year chronologically. The stage variable is defined as *k*. As for a long-term preventive maintenance plan for *K* years, *k* is 0, 1, 2, . . ., *K*.

2.3.2. State Variable

The target of multi-objective decision-making optimization is to allocate as few maintenance funds as possible for preventive maintenance of several or all composite pavement regions while maintaining the overall pavement performance in an acceptable state during the whole maintenance period. This study established two state variables: $s^1_{k=t,ni} = PCI_{k=t,ni}$ and $s^2_{k=t,ni} = c_{k=t,ni}$. $PCI_{k=t,ni}$ represents the current *PCI* of region *n* at the end of stage *t*, which is treated by maintenance technology *i* at the beginning of stage *t*. Furthermore, $c_{k=t,ni}$ represents the cumulative cost of maintenance technology *i*, which has been implemented in region *n* several times until the end of stage *t*.

2.3.3. Decision Variable

According to the aforementioned preventive maintenance technologies, six types of maintenance decisions are available for composite pavements (i.e., no maintenance, crack sealing, crack filling, fog seal, thin HMA overlay, and hot-mix recycled AC), and decision *i* is 0, 1, . . ., *I* (*I* = 5), respectively. For an airport with *N* composite pavement regions, the maintenance decision variable x_{kni} represents whether maintenance is implemented in region *n* (*n* = 1, 2, . . ., *N*) at stage *k*. Here, the maintenance decision variable x_{kni} is set to 0 if no preventive maintenance is implemented in the composite pavement region (*i* = 0); otherwise, x_{kni} is set to 1 if any of the five preventive maintenance technologies are adopted (*i* = 1 to 5).

2.3.4. State Transfer Variable

The state transfer equation describes the transformation from a certain state to the next being affected by the decision variable. According to the principle of DP, the state variable s_{k+1} in stage (k + 1) is entirely determined by the state variable s_k and decision variable x_k in stage k. The state transfer equation is expressed as $s_{k+1} = T_k(s_k, x_k)$. The decision variable x_k is 0 when no maintenance is implemented on composite pavements or 1 otherwise. Thus, the state transfer equation of s_k^1 and s_k^2 is a piecewise function related to x_k.

When x_k is 0 at the beginning of a stage, no maintenance is implemented on the composite pavement region, and thus, both the improvement of the *PCI* and the additional cost of maintenance are 0 until the next stage. As for $s^1_{k=t+1,n1}(PCI_{k=t+1,n1})$, if no preventive maintenance is implemented on region n at the beginning of stage (t + 1), its variation will follow the tendency of the $PCI_{k=t,ni}$ curve. $PCI_{t+1>k>t,n1}$ can be calculated based on Equations (1)–(6) and the 13 regression coefficients in Table 3, which vary as $ESAL$ during stage (t + 1). The state transfer equation of $s^1_{k=t+1,ni}$ (i = 0) is shown in Equation (10):

$$T^1_{t+1>k>t,ni} = s^1_{t+1>k>t,ni} - s^1_{k=t,ni} = PCI_{t+1>k>t,ni} - PCI_{k=t,ni} \tag{10}$$

As for $s^2_{k=t+1,n1}(c_{k=t+1,n1})$, it remains the same as $s^2_{k=t,n1}$ because of no additional maintenance costs in stage (t + 1). The state transfer equation of $s^2_{k=t+1,n1}$ is shown in Equation (11):

$$T^2_{t+1>k>t,ni} = s^2_{k=t+1,ni} - s^2_{k=t,ni} = c_{k=t+1,ni} - c_{k=t,ni} = 0 \tag{11}$$

When x_k is 1, certain maintenance is implemented on the composite pavement region, which influences both the deterioration tendency of *PCI* and the preventive maintenance cost. As for $s^1_{k=t+1,n1}(PCI_{k=t+1,n1})$, a jump in *PCI* (*PJ*) occurs immediately after maintenance, followed by a slower deterioration (*DRR*) during stage (t + 1). The $PCI_{k=t+1,n1}$ curve after various types of preventive maintenance can be calculated from corresponding *PJ* regression models and *DRR* statistical results. The state transfer equation of $s^1_{k=t+1,ni}$(i = 1 to 5) is the same as Equation (10).

As for $s^2_{k=t+1,n1}(c_{k=t+1,n1})$, it equals $s^2_{k=t,ni}$ plus $\Delta c_{k=t+1,ni}$, which is the additional maintenance cost in stage (t + 1). $\Delta c_{k=t+1,ni}$ is calculated based on Equation (12) considering inflation:

$$\Delta c_{k=t+1,ni} = \Delta c_{k=t,ni}(1 + R_{k=t}) = \Delta c_{k=1,ni}\prod_{k=1}^{t}(1+R_k) \tag{12}$$

where $\Delta c_{k=1,ni}$ is the cost of maintenance method i implemented in region n at the beginning of the initial stage (k = 1), and R_k is the inflation rate in stage k.

Thus, the state transfer equation of $s^2_{k=t+1,ni}$ (i = 1 to 5) is as shown in Equation (13):

$$T^2_{t+1>k>t,ni} = s^2_{k=t+1,ni} - s^2_{k=t,ni} = \Delta c_{k=1,ni}\prod_{k=1}^{t}(1+R_k) \tag{13}$$

2.3.5. Objective Function and Basic Equation

The objective function was used to estimate the maintenance decision in each stage, which is defined as $V_k(s_k, x_k)$ and consists of state variable s_k and decision variable x_k. $V_k(s_k, x_k)$ represents the total cumulative benefit or cost from stage k to the final stage. The basic equation $f_k(s_k)$ is the combination of all the optimum decisions from stage k to the final stage, which means it is the extremum of $V_k(s_k, x_k)$. The state transfer equation $T_k(s_k, x_k)$ represents the benefit and cost of each stage; therefore, $f_k(s_k)$ can be calculated based on a backward algorithm, as shown in Equation (14):

$$f_k(s_k) = opt\{V_k(s_k, x_k)\} = opt\{T_k(s_k, x_k) + f_{k+1}(s_{k+1})\},\ k = n,\ n-1,\ \ldots,\ 1 \tag{14}$$

Both the maximum total improvement in the *PCI* and minimum total maintenance cost from stage k to the final stage are required. The state transfer equations are used to calculate the average variation of PCI_{kni} and c_{kni} in stage k, as shown in Equations (15) and (16), respectively.

$$T_k^1(s_k^1, x_k) = \frac{1}{N}\sum_{n=1}^{N}\sum_{i=0}^{I}(s_{kni}^1 - s_{(k-1)ni}^1)x_{kni} = \frac{1}{N}\sum_{n=1}^{N}\sum_{i=0}^{I}\Delta PCI_{kni}x_{kni} \tag{15}$$

$$T_k^2(s_k^2, x_k) = \frac{1}{N}\sum_{n=1}^{N}\sum_{i=0}^{I}(s_{kni}^2 - s_{(k-1)ni}^2)x_{kni} = \frac{1}{N}\sum_{n=1}^{N}\sum_{i=0}^{I}\Delta c_{kni}x_{kni} \tag{16}$$

where ΔPCI_{kni} and Δc_{kni} are calculated based on Equations (10)–(13).

Thus, the basic equations are as follows:

$$f_k^1(s_k) = \max\left\{T_k^1(s_k, x_k) + f_{k+1}^1(s_{k+1})\right\} \tag{17}$$

$$f_k^2(s_k) = \min\left\{T_k^2(s_k, x_k) + f_{k+1}^2(s_{k+1})\right\} \tag{18}$$

2.3.6. Constraint

In view of the preventive maintenance requirement, four constraints were established: (1) x_{kni} is either 0 or 1; (2) a maximum of one maintenance technology can be implemented in each region per stage; (3) the *PCI* must not exceed the range between the minimum acceptable value ($PCI_{\min}$) and 100; and (4) the maintenance cost is not negative and the sum of all the regions must not exceed the annual maintenance budget $C_{\max,k}$. These constraints are presented as follows:

$$x_{kni} = 0 \text{ or } 1 \tag{19}$$

$$\sum_{i=0}^{I} x_{kni} \le 1 \tag{20}$$

$$PCI_{\min} \le \overline{PCI}_k = \frac{1}{N}\sum_{n=1}^{N}\sum_{i=0}^{I} PCI_{kni}x_{kni} \le 100 \tag{21}$$

$$0 \le C_k = \sum_{n=1}^{N}\sum_{i=0}^{I}\Delta c_{kni}x_{kni} \le C_{\max,k} \tag{22}$$

2.4. Optimization Incremental Dynamic Programming Algorithm

Multi-objective decision-making optimization based on DP is a multi-stage solution process. Incremental DP (IDP) is a widely used backward algorithm from the final stage to the initial stage. In other words, the maintenance decision of the final stage is made first, followed by that of the former stage successively. Finally, decisions for all stages are made, and the long-term maintenance plan is completed during the entire period. Considering both remaining pavement service performance and reducing the influence of inflation, maintenance should be implemented at the beginning of each stage. Thus, the *PCI* at the beginning of stage k ($s_{kni}^1{'}$) equals the *PCI* at the end of stage $(k-1)$ ($s_{(k-1)ni}^1$) plus the *PJ* calculated from the regression models. Moreover, the *PCI* at the end of stage k (s_{kni}^1) equals $s_{kni}^1{'}$ minus the deterioration value, which is less than that with no maintenance by *DRR* (%).

In the first step of iterative computation based on IDP, $s_{k=K,n,i=1}^1$ and $s_{k=K,n,i=1}^2$ at the final stage, are calculated from the state transfer equation when x_{kni} is 0, which means no maintenance is implemented during the whole planning period. This is the most economical maintenance plan because of zero cost, but it perhaps does not meet the requirement of $PCI_{\min}$. Thus, the implementation of some maintenance technology may be required in advance. The maintenance decision combination of all the regions in stage k is $p_k = \begin{bmatrix} i_{n=1} & i_{n=2} & \cdots & i_{n=N} \end{bmatrix}$. The set of non-inferior solutions in stage K consists of all p_K satisfying constraints from Equations (19)–(22). The optimal solution p_K^* is determined as shown in Figure 1, where the dots represent the C_K and $\overline{PCI}_K$ corresponding to each p_K; the horizontal and vertical lines represent the limits of $C_{\max,K}$ and $PCI_{\min}$; and the dashed oblique line is the optimal split line. The vertical distance between the dot and the optimal split line is positive if the dot is above the line otherwise the opposite is true. Furthermore, p_K^* corresponds to the dot where the maximum vertical distance exists.

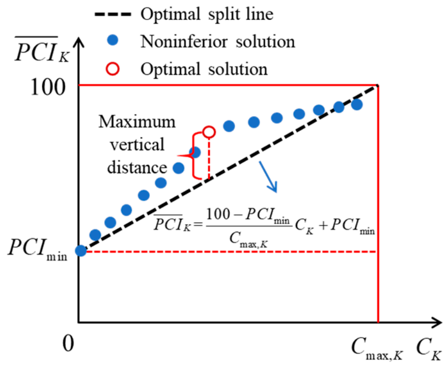


Figure 1. Non-inferior solutions and the optimal solution.

In the subsequent steps, the set of non-inferior solutions in stage k ($k < K$) consists of p_k and $p_{k+1}^*, \ldots, p_K^*$, and p_k^* is determined using the same method. Based on the IDP backward algorithm, the optimal preventive maintenance plan could be determined, which is a combination of $p_1^*, \ldots, p_K^*$.

For composite pavement consisting of N regions, which can be treated using I types of maintenance technology, there are $(I+1)^N$ types of decision combinations per stage as well as numerous calculations. In terms of long-term preventive maintenance decision-making, calculation costs must be reduced via optimizing the IDP algorithm. IDP consists of two parts: a set of non-inferior solutions and the optimal solution. The two calculation processes were optimized as follows.

In the calculation process of non-inferior solutions, some p_k may exceed the constraint of $C_{\max,k}$, or different p_k may correspond to the same $\overline{PCI}_k$ and C_k. Taking a 3-year preventive maintenance plan as an example, the composite pavement consists of three regions and two available maintenance technologies. $PCI_{\min}$ is 90 and $C_{\max,k=3}$ is 13, and the costs of the three decision variables x_0, x_1, and x_2 are 0, 5, and 8, respectively. Furthermore, the PJ is 0, 4, and 6, respectively, when PCI_b is 94. Figure 2a plots the deterioration of the PCI. Considering the constraint $C_{\max,k=3} = 13$, 16 decision combinations are available, much fewer than that (3^3 = 27 combinations) without $C_{\max,k=3}$. The 16 $p_{k=3}$ correspond entirely to five types of non-inferior solutions, as shown in Figure 2b. For example, the dot (10, 92.67) corresponds to the three decision combinations where maintenance I (x_1) is implemented on any two regions, and the other is not treated. Thus, calculating all non-inferior solutions is unnecessary.

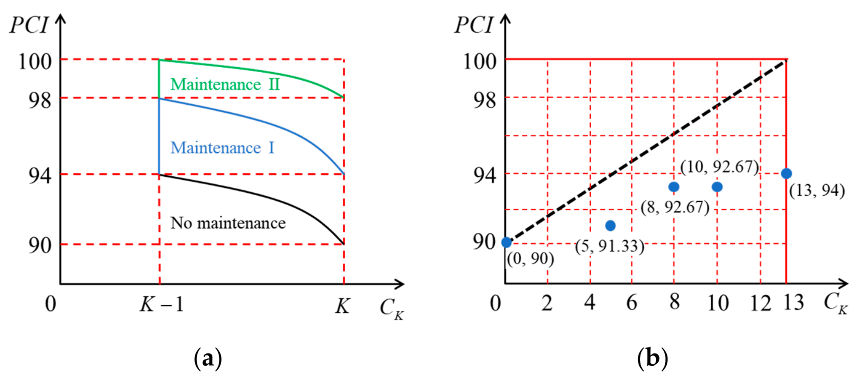


Figure 2. Calculation example of non-inferior solutions. (**a**) PCI curves; (**b**) Non-inferior solutions.

In light of the aforementioned information, the calculation process of non-inferior solutions is optimized as follows. First, the decision combinations with C_k over $C_{\max,k}$

are excluded in advance to avoid the unnecessary calculation of $\overline{PCI}_k$. On the other hand, one of the decision combinations corresponding to the same C_k and $\overline{PCI}_k$ is selected randomly to calculate the vertical distance to the optimal split line, thereby avoiding repetitive calculations.

In the calculation process of the optimal solution, the maximum vertical distance must be determined. Considering that $\overline{PCI}_k$ monotonically increases as C_k increases, a median approach algorithm is proposed to reduce calculation times. This algorithm approaches the optimal solution by bisecting the possible interval step by step. Figure 3 shows the steps for determining the optimal solution. First, the vertical distances to the optimal split line of the two boundary dots (① and ②) are determined. Then, the dot that is the closest to the middle of the non-inferior solution interval is defined as the median dot (③), and its distance is calculated. Next, the distance of the median dot is compared with those of the boundary dots; if the former is larger than any of the latter, the closer boundary dot is replaced with the median dot, thereby establishing the new non-inferior solution interval (① and ③). Finally, these steps are repeated until there are only two boundary dots or three dots, including the newest median dot, and the optimal solution is determined (⑥). As shown in Figure 3, there are a total of 6 dots with vertical distances to the optimal split line that must be calculated, which is much fewer than that in the original IDP algorithm.

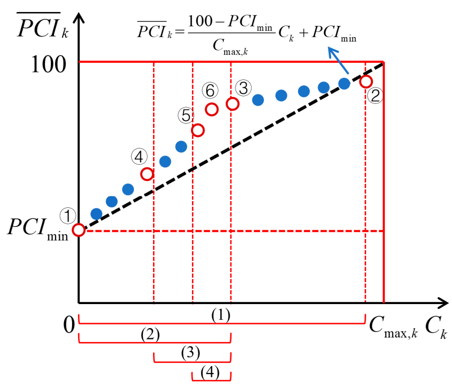


Figure 3. The median approach algorithm of the optimal solution.

3. Results and Discussion

3.1. *Performance Deterioration of Runway Composite Pavement Regions*

This study surveyed five typical airports in China with composite pavements. Table 1 presents their structural and traffic conditions. In Table 1, CZX represents Changzhou Benniu Airport, DLC represents Dalian Zhouzishui Airport, TAO represents Qingdao Liuting Airport, XMN represents Xiamen Gaoqi Airport, and SHA represents Shanghai Hongqiao Airport according to International Air Transport Association (IATA) codes.

Table 1. Structural and traffic conditions of the investigated airports.

Airport Code	Airport Region	Year of AC Overlay	Thickness of AC Overlay (cm)	Thickness of PCC Pavement (cm)	h_e (cm)	Years of Traffic Investigated	*ESAL* (/day)
CZX	Middle runway	2013	SMA-13: 5 AC-20: 11	42	39.89	2013–2017	31
	Taxiway		SMA-13: 5 AC-20: 12.5	56	51.58		8
DLC	Middle runway	2005	SMA-16: 6 AC-21: 15	32	34.11	2007–2011	93
	Terminal runway		SMA-16: 6 AC-21: 10	37	35.95		47
	Taxiway		SMA-16: 6 AC-21: 6 AC-25: 9	32	34.11		19

Table 1. *Cont.*

Airport Code	Airport Region	Year of AC Overlay	Thickness of AC Overlay (cm)	Thickness of PCC Pavement (cm)	h_e (cm)	Years of Traffic Investigated	*ESAL* (/day)
TAO	Middle runway	2010	SMA-16: 6 AC-20: 7	32	30.74	2013–2017	320
	Terminal runway		SMA-16: 6 AC-20: 12	34	34.42		160
	Taxiway		SMA-16: 6 AC-20: 12	34	34.42		54
XMN	Middle runway	2008	SMA-16: 6 AC-20: 16	30	32.95	2011–2015	135
	Terminal runway		SMA-16: 6 AC-20: 14	30	32.11		68
	Taxiway		SMA-16: 6 AC-20: 12	33	31.26		27
SHA	Middle runway	2011	SMA-13: 5 AC-16: 7 SMA-16: 6 AC-20: 19	38	44.79	2012–2016	357
	Terminal runway		SMA-13: 5 AC-16: 7 SMA-16: 6 AC-20: 19	31	40.15		179

Figure 4 plots the *PCI* curves of different regions in the five investigated airports. The *PCI* data were collected manually on-site every four years.

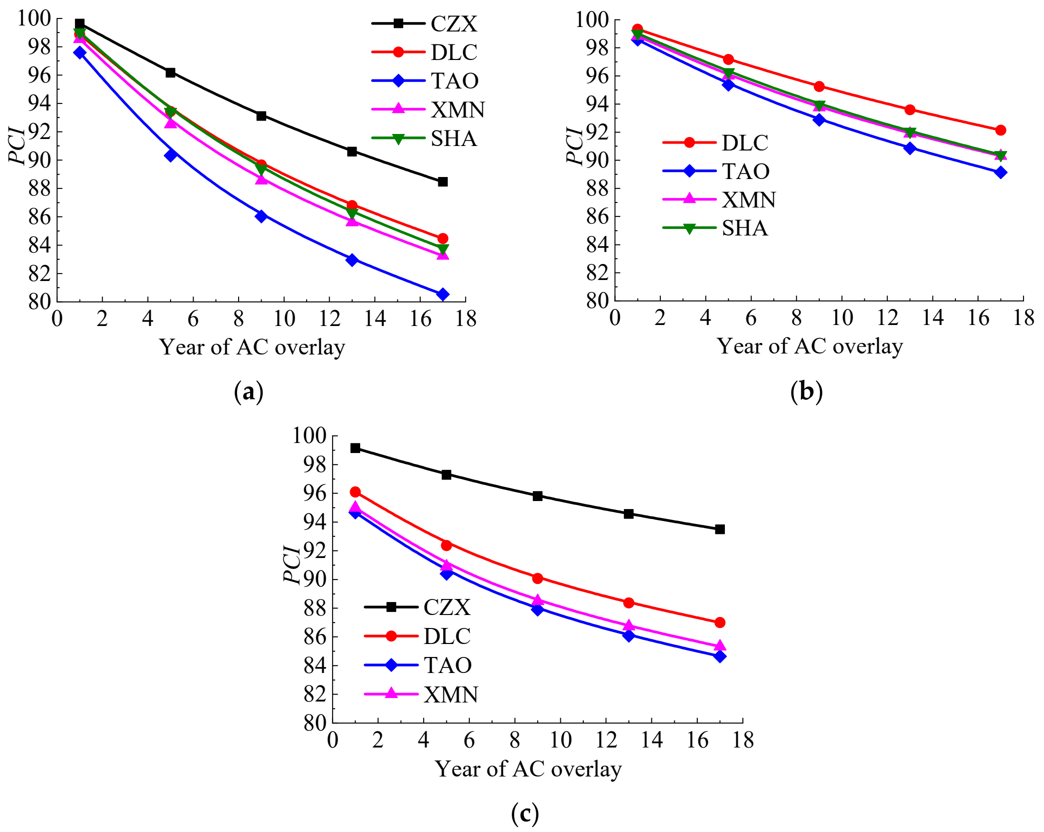


Figure 4. *PCI* deterioration curves of different composite pavement regions. (**a**) Middle runway; (**b**) Terminal runway; (**c**) Taxiway.

According to the PCI curves of different airports and regions, the deterioration rate of PCI increases as h_e decreases and $ESAL$ increases. In Equation (1), the factors α and β are regressed by various PCI, y, h_e, and $ESAL$, as shown in Table 2. The 13 coefficients a_n, b_n, c_n, and d in Equations (3)–(6) are regressed by various α, β, h_e, and $ESAL$, as shown in Table 3.

Table 2. α and β in PCI regression curves.

Region of the Airport	Airport Code	α	β
Middle runway	CZX	167.6163	0.3366
	DLC	125.9302	0.3105
	TAO	92.5086	0.2906
	XMN	114.7053	0.3041
	SHA	104.9870	0.3287
Terminal runway	DLC	187.4970	0.3074
	TAO	133.8690	0.2955
	XMN	160.0943	0.2944
	SHA	140.8225	0.3094
Taxiway	CZX	478.9010	0.2529
	DLC	264.9978	0.2108
	TAO	196.3031	0.2037
	XMN	226.6756	0.2021

Table 3. Regression coefficients.

Region of Airport	Regression Coefficients						
	a_1	b_1	c_1	a_2	b_2	c_2	
Middle runway	23.9802	0.8943	−0.2087	194.3201	−2.8224	−0.0845	
Terminal runway	24.1403	0.8423	−0.2246	183.1502	−2.1321	−0.0912	
Taxiway	31.9805	0.8217	−0.2456	171.2804	−1.8321	−0.0972	
Region of Airport	**Regression Coefficients**						
	a_3	b_3	c_3	a_4	b_4	c_4	d
Middle runway	1.1020	−0.2411	−0.0803	0.0453	0.3349	−0.0255	−0.0981
Terminal runway	1.4210	−0.2121	−0.0942	0.0557	0.3144	−0.0211	−0.0975
Taxiway	1.5691	−0.2033	−0.0987	0.0418	0.3578	−0.0311	−0.0985

3.2. Maintenance Benefits of Preventive Maintenance Maintenance Technologies

3.2.1. Performance Jump

Figure 5 plots PJ-PCI_b fitting curves, regression models (Equation (9)), and coefficients of determination R^2 for the five maintenance methods. The relevance between PJ and PCI_b is higher than 0.87 when composite pavements are treated with the five maintenance technologies, which, in order of increasing relevance, are crack sealing, crack filling, fog seal, thin HMA overlay, and hot-mix recycled AC. According to the five regression models of PJ and PCI_b, the improvements in composite pavement performance after treatment with the different maintenance technologies could be calculated.

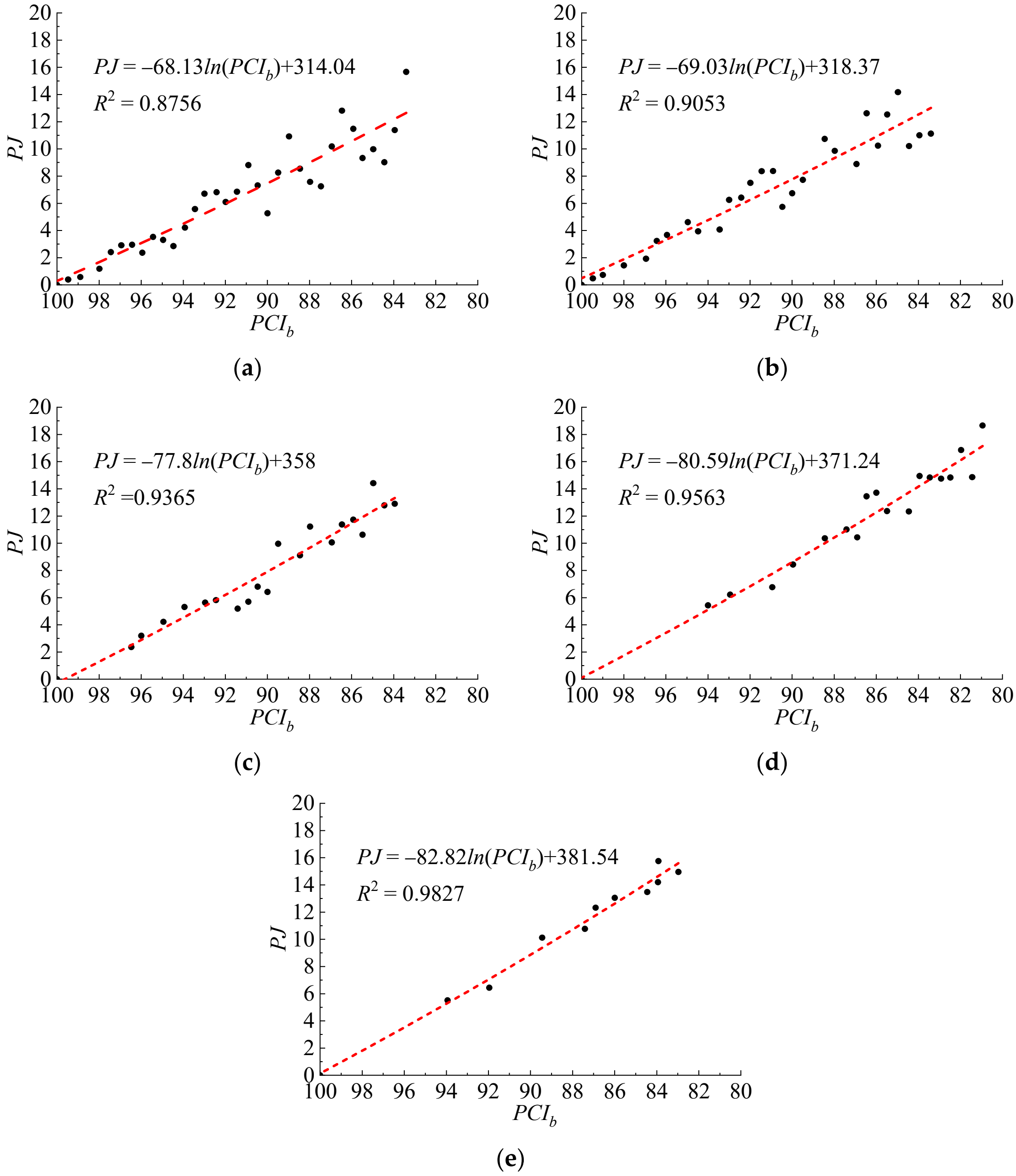


Figure 5. *PJ* versus PCI_b of sections treated with five different preventive maintenance technologies. (**a**) Crack sealing; (**b**) Crack filling; (**c**) Fog seal; (**d**) Thin HMA overlay; (**e**) Hot-mix recycled AC.

3.2.2. Deterioration Rate Reduction

Figure 6 shows the deterioration rates of *PCI* before and after the five types of preventive maintenance, as well as the *DRR* of each technology. The vertical dashed line represents the year of maintenance, and the solid line is divided into two parts by this dashed line. The left part is the deterioration rate of *PCI* before maintenance, which was calculated according to the difference of *PCI* in continuous years, whereas the right part is the deterioration rate of *PCI* without maintenance, which was predicted according to the tendency of the fitting curve. The dashed line represents the *PCI* deterioration rate after maintenance. The *PCI* in each year was calculated according to the performance data in the LTPP database. The *DRR* is the relative difference between the *PCI* deterioration rates immediately before and after maintenance [40].

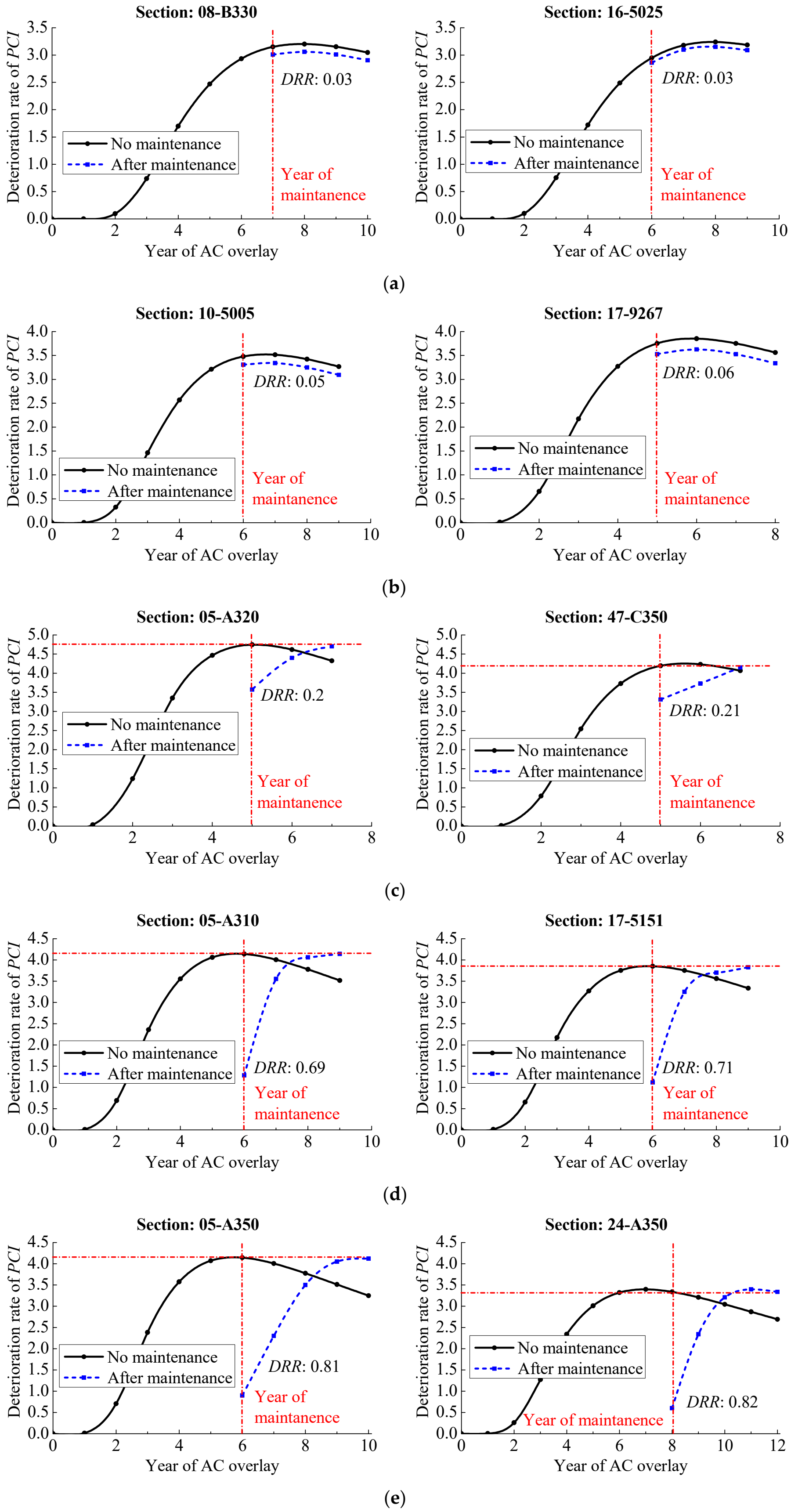


Figure 6. Deterioration rate of *PCI* versus year of AC overlay of sections treated with various preventive maintenance technologies. (**a**) Crack sealing; (**b**) Crack filling; (**c**) Fog seal; (**d**) Thin HMA overlay; (**e**) Hot-mix recycled AC.

Figure 6a,b show the deterioration rates of *PCI* and *DRR* of representative sections after crack sealing and crack filling, respectively. The *DRR* of all 61 sections is small, or 0.01 in order of magnitude. Furthermore, the tendency of the deterioration rate of *PCI* after crack sealing or crack filling is similar to that without maintenance. Therefore, crack sealing and crack filling rarely influence the deterioration rates of the *PCI* or *DRR* of composite pavement.

Figure 6c shows the deterioration rates of *PCI* and *DRR* of representative sections treated with fog seal. The average *DRR* of the 21 sections treated with fog seal is approximately 0.2. After 2 years of maintenance, the *PCI* deterioration rate increases to that just before maintenance, indicating that the fog seal has an influence on the *DRR* for 2 years after maintenance. The deterioration rate of *PCI* declines by 20% in the year of fog seal maintenance, and that after n (n = 1, 2) years of maintenance is approximately equal to that $(2 - n)$ years before maintenance.

Figure 6d shows the deterioration rates of *PCI* and *DRR* of representative sections treated with a thin HMA overlay. The average *DRR* of the 19 sections treated with a thin HMA overlay is approximately 0.7. After 3 years of maintenance, the deterioration rate of *PCI* increases to that just before maintenance, indicating that thin HMA overlay has an influence on the *DRR* for 3 years following maintenance. The deterioration rate of *PCI* declines by 70% in the year of HMA maintenance, and the deterioration rate of *PCI* after n (n = 1, 2, 3) years of maintenance is approximately equal to that $(3 - n)$ years before maintenance.

Figure 6e shows the deterioration rates of *PCI* and *DRR* of representative sections treated with hot-mix recycled AC. The average *DRR* of the 19 sections treated with hot-mix recycled AC is approximately 0.8. After 4 years of maintenance, the deterioration rate of *PCI* increases to that just before maintenance, indicating that hot-mix recycled AC has an influence on the *DRR* for 4 years after maintenance. The deterioration rate of *PCI* declines by 80% in the year of hot-mix recycled AC maintenance, and the deterioration rate of *PCI* after n (n = 1, 2, 3, 4) years of maintenance is approximately equal to that $(4 - n)$ years before maintenance.

3.3. Application of Long-Term Maintenance Decision-Making Optimization Method

Based on the abovementioned decision-making optimization method, this study implemented a five-year preventive maintenance plan on Sunan Shuofang Airport (WUX), China, which featured eight composite pavement regions.

3.3.1. Decision-Making Model Parameters

In 2010, AC overlay was paved onto PCC pavement at Sunan Shuofang Airport when the *PCI* was 100. Table 4 presents the structural and traffic conditions of the eight regions.

Table 4. Structural and traffic conditions of Sunan Shuofang Airport.

Region Code	Region of Airport	h_e (cm)	*ESAL* (/day)
1#/2#/3#/4#	Terminal runway	36	39
5#/6#/7#/8#	Middle runway	39	58

The maintenance period from 2013 to 2017 was divided into five stages at intervals of 1 year (K = 5). According to the maintenance history, crack filling, fog seal, and hot-mix recycled AC were available, corresponding to $x_{kn,i=2}$, $x_{kn,i=3}$, and $x_{kn,i=5}$, respectively. Considering both the maintenance benefit and inflation influence, preventive maintenance must be implemented as soon as possible, and therefore, the maintenance decision was made at the beginning of each stage. According to the previous maintenance history, preventive maintenance was completed quickly; thus, the maintenance time was set as 0 to simplify calculations.

The annual average inflation rates in China for each year from 2013 to 2017 were 2.35, 1.98, 1.52, 2.07, and 1.47%, respectively. According to the preventive maintenance costs [41,42], the cost in each stage can be calculated and the $\Delta c_{k=5,ni}$ is as shown in Table 5. Considering the pavement performance requirement and the annual maintenance budget limit, the $PCI_{\min}$ is 90 and $C_{\max,k}$ is $64,000.

Table 5. Cost of preventive maintenance in stage 5.

Maintenance Technology	Unit Cost	Maintenance Length/Area	Total Costs ($\Delta c_{k=5,ni}$)
Crack filling	$2.4/m	11,000 m	$26,400
Fog seal	$3.3/m^2	9000 m^2	$29,700
Hot-mix recycled AC	$4.0/m^2	9000 m^2	$36,000

3.3.2. Maintenance Decision-Making Solution

According to the *PCI* predictive model (Equations (1)–(6)) and the model parameters in Tables 3 and 4, the average *PCI* of the terminal runway and middle runway will be 88.4 and 83.9 at the end of stage 5, respectively, if no maintenance has been implemented during the whole period. Due to $PCI_{\min}$, some maintenance must be implemented in advance. Based on the optimization IDP algorithm, the non-inferior solutions from stages 5 to 1 are shown in Figure 7. Figure 7 indicates that the optimal solution for each stage is "no maintenance." However, considering the constraint $PCI_{\min} = 90$, preventive maintenance should be implemented in the early stages when it is more economical.

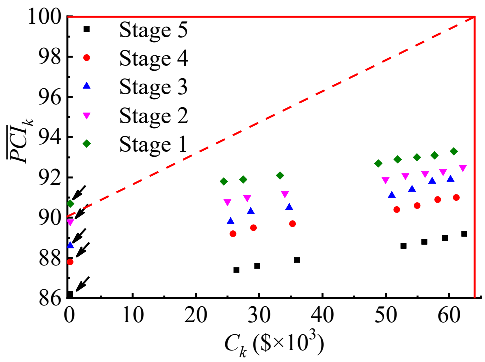


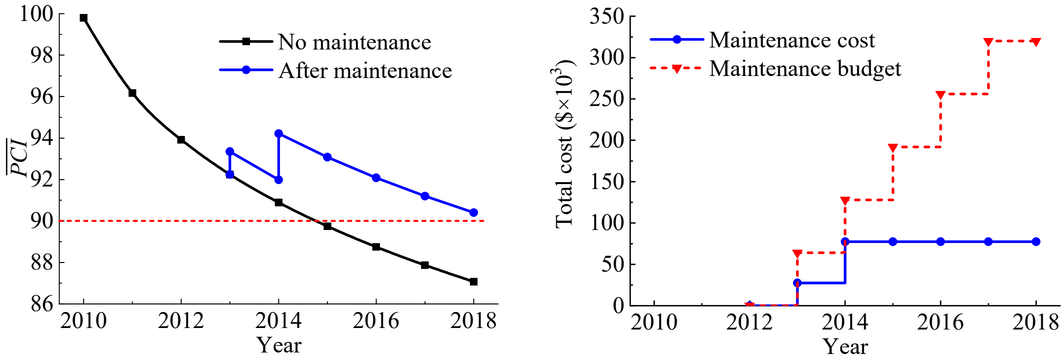
Figure 7. Non-inferior solutions of each stage.

Table 6 lists the benefit–cost rates of various maintenance-decision combinations in stage 1. Maintenance decision combination 2 ($p_{k=1} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 2 \end{bmatrix}$), which has the maximum benefit–cost rate, is the optimal solution, but the increase in $\overline{PCI}_{k=5}$ is inadequate to meet the requirement of $PCI_{\min}$. Thus, maintenance is still required in stage 2, and the optimal decision combination is $p_{k=2} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 \end{bmatrix}$. In sum, the optimal maintenance plan for Sunan Shuofang Airport is treating region 8# with fog seal in 2013 and treating regions 6# and 7# with crack filling in 2014.

Table 6. Benefit–cost rates of $p_{k=1}$.

No.	$p_{k=1}$	$C_{k=1}$($)	Increase in $\overline{PCI}_{k=5}$	Benefit–Cost Rate ($\times 10^{-5}$)
1	[0, 0, 0, 0, 0, 0, 0, 2]	24,409	0.97	3.97
2	[0, 0, 0, 0, 0, 0, 0, 3]	27,460	1.11	4.04
3	[0, 0, 0, 0, 0, 0, 0, 5]	33,285	1.28	3.85
4	[0, 0, 0, 0, 0, 0, 2, 2]	48,818	1.95	3.99
5	[0, 0, 0, 0, 0, 0, 2, 3]	51,869	2.08	4.01
6	[0, 0, 0, 0, 0, 0, 3, 3]	54,920	2.21	4.02
7	[0, 0, 0, 0, 0, 0, 2, 5]	57,694	2.25	3.90
8	[0, 0, 0, 0, 0, 0, 3, 5]	60,745	2.39	3.93

The average *PCI* value of composite pavements and the maintenance costs during the whole period are shown in Figure 8. Based on the abovementioned decision-making optimization method, this study's five-year preventive maintenance plan not only sufficiently meets the demand for pavement performance but also spends maintenance funds properly without exceeding the budget.



(**a**) (**b**)

Figure 8. The five-year maintenance plan for Sunan Shuofang Airport. (**a**) Average *PCI* curves; (**b**) Maintenance cost.

4. Conclusions

This study analyzed the composite pavement performance deterioration of airports investigated, as well as the benefits of typical preventive maintenance technologies according to *LTPP* data. Furthermore, this study proposed an optimization IDP algorithm for long-term preventive maintenance decision-making. Key findings and conclusions are as follows:

1. The *PCI* deterioration tendencies of the middle runway, terminal runway, and taxiway in five airports with composite pavements were analyzed, and the corresponding *PCI* predictive models were regressed according to the long-term data of the investigated airports. The 13 coefficients a_n, b_n, c_n (n = 1, 2, 3, 4), and d in the *PCI* predictive models for different composite pavement regions are shown in Table 3.
2. According to the LTPP database, *PJ*, *DRR*, and *PCI* deterioration rates of 33 composite pavement sections treated with crack sealing, 28 with crack filling, 21 with fog seal, 19 with thin HMA overlay, and 11 with hot-mix recycled AC were analyzed. Thus, the maintenance benefit of each maintenance technology was determined. The regression relationship between *PJ* and *PCI* immediately before maintenance is shown in Figure 5, using a logarithmic model. For sections treated with crack sealing and crack filling, the DRR is nearly 0, and the *PCI* deterioration rate is rarely influenced. For sections treated with fog seal, the average *DRR* is 0.2, and the reduced *PCI* deterioration rate returns to that immediately before maintenance after 2 years. For sections treated with thin HMA overlay and hot-mix recycled AC, the average *DRR* is 0.7 and 0.8, and the recovering time of *PCI* deterioration rate is 3 and 4 years, respectively.
3. A decision-making optimization method for long-term preventive maintenance based on DP was proposed, and the DP model parameters include stage variables, state variables, decision variables, state transfer equations, objective functions, basic equations, and constraints. An optimization IDP algorithm was developed to reduce the calculation cost by optimizing the calculation processes of both non-inferior solutions and the optimal solution. A method was used for preprocessing non-inferior solutions, and a median approach algorithm was proposed to reduce the time needed to compute the optimal solution. The decision-making optimization method was applied in a five-year preventive maintenance plan for composite pavements in Sunan Shuofang Airport, China, which sufficiently meets the demand for pavement performance without exceeding the annual maintenance budget.

4. In this study, which maintenance technologies to adopt and when to maintain the pavement were dependent on the condition and deterioration tendency of composite pavements. Furthermore, the treatment costs were dependent on the type of maintenance technologies and inflation. However, the treatment costs were assumed to be irrelevant to composite pavement conditions, although poorer conditions may require greater treatment costs for the same maintenance technology. Moreover, the penalty for the maintenance of aircraft because of poor runway conditions, which may exacerbate aircraft deterioration and increase airline company costs, was not considered. These assumptions resulted in yielding "no maintenance" as the optimal solution in the application. The aforementioned problems must be studied in future work, including the relationship between treatment costs and pavement condition, as well as the more comprehensive constraints in the maintenance decision-making optimization method.

Author Contributions: Conceptualization, J.L.; methodology, Z.W.; validation, S.L.; formal analysis, Z.W.; investigation, Z.W.; resources, S.L.; data curation, S.L.; writing—original draft preparation, Z.W. and Y.T.; writing—review and editing, Z.W. and Y.T.; supervision, J.L.; project administration, J.L.; funding acquisition, J.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Natural Science Foundation of China (Grant No. U1433201 and No. U2333208).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The pavement distress survey and maintenance benefit data used during the study were provided by the Key Laboratory of Infrastructure Durability and Operational Safety in Airfields of the Civil Aviation Administration of China and the Long-term Pavement Performance Program, respectively. Direct requests for these materials may be made to the provider, and they are available from the corresponding author upon reasonable request. All models and codes used during the study appear in the submitted article.

Acknowledgments: The authors very much appreciate the data provided by the Key Laboratory of Infrastructure Durability and Operation Safety in the Airfield of Civil Aviation Administration of China and the Long-term Pavement Performance program. The authors very much appreciate the contribution of Penghui Li to the software and data curation parts of the article.

Conflicts of Interest: The authors declare no conflicts of interest.

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