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Optimum Maintenance and Rehabilitation Decision Making Considering Delay Effects for Airport Pavement Management

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Abstract: A chance-constrained programming methodology, considering delay effects, is proposed to find maintenance and rehabilitation (M&R) polices for airport pavement management under parameters uncertainty. This is accomplished with a Monte Carlo (MC) simulation-based genetic algorithm (GA) approach. MC is used to tackle the probabilities of object function and constraints while GA is used to obtain an optimization sequence. Delay cost (C_D) is integrated in M&R decision models. A case study is presented. It is shown that chance-constrained programming is more reliable than the expected value model. Optimum refurbishment timing and delay effects on M&R policies are also investigated.

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***Key words**: Air traffic delay; Chance-constrained programming; Pavement maintenance and rehabilitation; Pavement management; Simulation Optimization.*

Introduction

One of the major requirements of an airport pavement management system (APMS) is the ability to develop a pavement maintenance program for the airport agency. The problem of making optimal maintenance and rehabilitation (M&R) policy decision has been studied by a number of researchers. One common class of models is based on the assumption that the parameters, including pavement deterioration, improvements of the pavement, user and agency cost estimation [1-3], are of complete certainty. Unfortunately, the assumption of determinism is questionable. For example, pavement performance depends on many parameters, such as environmental conditions, traffic, and material, making it difficult, if not impossible, to develop an accurate pavement performance prediction model. The uncertainties of parameters contribute to the reliability of the pavement maintenance plan. Hence, these uncertainties should be carefully considered.

To incorporate stochasticity in the determination of optimal M&R policy, alternative models have been proposed. As Ng (2011) [4] said, "The most popular class of models that explicitly account for the stochastic nature of the M&R problem is based on the theory of Markov Decision Processes (MDP)". Golabi et al. (1982) originally introduced MDP into the pavement maintenance decision making when designing the pavement management system for Arizona State [5]. In the ensuing decades, different pavement M&R models (e.g. Carnahan, 1987 [6]; Gopal, 1991 [7]; Smilowitz and Madanat, 2000 [8]) based on MDP are devised. However, assumptions of MDP are inconsistent with the actual conditions. For example, it is assumed that the transition matrix accurately describes the deterioration of performance. Therefore, many researchers try to modify the traditional MDP models or propose a new class of models.

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To the best of our knowledge, Chootinan et al. (2006) [9] first proposed the chance-constrained models based on the continuous stochastic prediction formulations when making a multi-year pavement maintenance plan for the entire road network. However, most of the models mentioned above point at road pavement, and differences [10] exist between airport and roadway pavement management, including the size of networks, operation procedures, and so on. For instance, the pavement condition of road networks is usually investigated by sampling, instead of complete monitoring for the airfield network. Moreover, maintenance activities could be completed without closing traffic for the road network. However, repair actions are typically done at night when the air traffic is closed except for emergencies for the airfield network. It means that it is necessary to develop the M&R models for APMS considering airports' individual characteristics. In this paper, a chance-constrained programming methodology, considering delay effects, is devised to find M&R polices for airport pavement management under parameters uncertainty.

The section "Maintenance Cost and Effectiveness Model" presents the agency cost model, user cost model, and maintenance effectiveness model. M&R decision making models are proposed in the sections following. The MC simulation-based genetic algorithm (GA) approach is then detailed. In addition, an actual case is given, and in the final sections, study conclusions and major findings are presented.

Methodology

Maintenance Cost and Effectiveness Model

Before introducing M&R policy models, let us, for the sake of completeness, begin with the definition of pavement maintenance cost and effectiveness.

It is well known that the total cost of pavement maintenance (C) equals the sum of agency cost (C_A) and user cost (C_U).

Agency Cost Model

The agency cost (C_A) consisits of routine maintenance cost (C_{A1}), periodical refurbishment cost (C_{A2}), and the salvage value (C_S), so we have:

$$C_A = C_{A1} + C_{A2} - C_S \tag{1}$$

$$\begin{cases} C_{A1} \sim N(\mu_{A1}, \sigma_{A1}^2) \\ \sigma_{A1} = \mu_{A1}/10 \\ \mu_{A1} = \begin{cases} 5(RMB \cdot m^{-2}) & \text{PCI} \geq 90 \\ 5 + 0.5 \times (90 - PCI)(RMB \cdot m^{-2}) & 90 > PCI \geq 50 \\ 25(RMB \cdot m^{-2}) & \text{PCI} < 50 \end{cases} \end{cases} \tag{2}$$

C_{A1} is considered related to maintenance level and pavement condition (Pavement Condition Index (PCI) is considered as the evaluation index of pavement condition here). The maintenance level is divided into three ranks: high, medium, and low. It is assumed that C_{A1} under medium and low maintenance level is 60 percent and 30 percent, respectively, of that under high maintenance level. Also, C_{A1} is assumed to follow the *normal distribution*. The relationship between C_{A1} under high maintenance level and PCI is shown in Eq. (2).

Based on the calculation method of MicroPAVER5.2 [11], the relationship between C_{A2} and PCI is shown in Eq. (3), with reference to the regulation of Civil Aviation Administration of China (CAAC) [12] and engineering experiences of three airports in China. For large hub airports, it is often required that refurbishing must not influence the operation of flights. In this case, C_{A2} usually gets a slight increase and is valued in the growth rate at 5 percent for runways [12].

$$\begin{cases} C_{A2} \sim N(\mu_{A2}, \sigma_{A2}^2) \\ \sigma_{A2} = \mu_{A2}/10 \\ \mu_{A2} = \begin{cases} 200(RMB \cdot m^{-2}) & \text{PCI} \geq 80 \\ 200 + 8 \times (80 - PCI)(RMB \cdot m^{-2}) & 80 > PCI \geq 30 \\ 600(RMB \cdot m^{-2}) & \text{PCI} < 30 \end{cases} \end{cases} \tag{3}$$

The salvage value (C_S), which is a function of the latest refurbishment cost, is shown in Eq. (4). S represents salvage life and T designing life of the overlay.

$$C_s = \left(1 - \frac{S}{T}\right) C_{A2} \tag{4}$$

User Cost Model

Considering the difficulties of estimating the delay cost precisely, user cost (C_U) depends on delay cost (C_D) here. Calculation methods and charts of delay cost (C_D) are proposed in FAA.AC 150/5060-5 [13]. McNerney et al. (1995) [14] analyze the influence of pavement maintenance engineering, and Lary (1991) [15] found that the delay cost was about 110,000 -131,000 US dollars by the analysis of a case. Using Taiwan Taoyuan International Airport as an example, Zhen (2007) [16] gives the airport with two runways a strategy, considering delay cost, when one runway is closed for reconstruction. Zou and Madanat (2011) [17] study the delay effects due to maintenance and repair actions for airports with multiple runways.

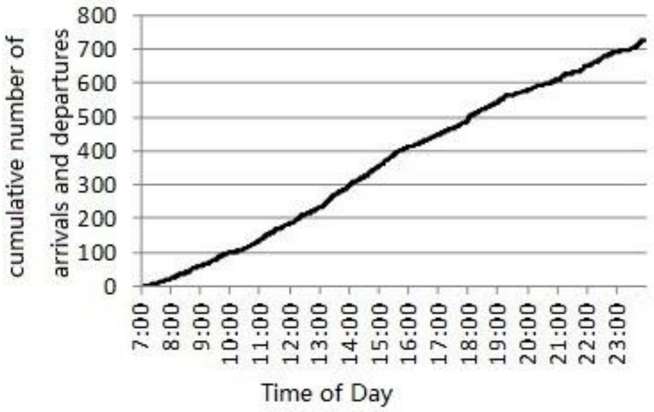

Fig. 1. Cumulative Number of Arrivals and Departures for a Sample Day Schedule at Sample Airport in Eastern China [18].

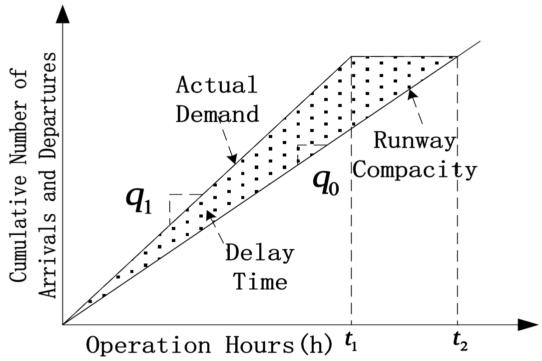

Fig. 2. Illustration of Delay Effects.

Routine maintenance and repair action is usually taken during the night when the airport is closed in China. In this situation, the operation of airport will not be influenced. The delay effects caused by reconstructing the taxiway and apron are not considered in this paper. Also, the delay time is defined as the area between the actual demand and capacity.

For large hub airports, it is assumed that arrivals and departures obey uniform distributions during the operation hours, as shown in Figs. 1 and 2. Hence, delay time is formulated in Eq. (5). q_0 and q_1, respectively, represent actual and design average arrival demand.

$$D = \frac{\int_0^{t_1} q_1 dt (t_2 - t_1)}{2} = \frac{q_1 t_1^2}{2}\left(\frac{q_1}{q_0} - 1\right) \qquad (q_1 > q_0) \tag{5}$$

Given the airline delay cost for each hour, C_1, and the passenger delay cost obtained by multiplying the passenger value of time, C_2, and the average number of passengers on an airplane P, the total delay cost could be presented as Eq. (6) shows.

$$C_D = (C_1 + C_2 \times P)D \tag{6}$$

Estimation of delay cost has been studied by numerous researchers [19-23]. Considering the actual operation condition, C_1 and C_2 are respectively valued as 12,000 RMB/h and 150 RMB/h.

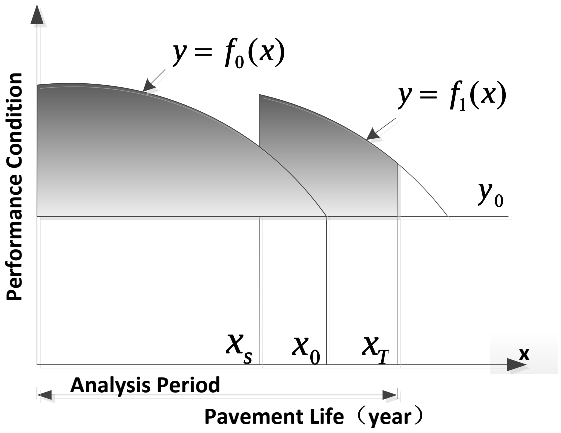

Fig. 3. PCI versus Pavement Life.

Maintenance Effectiveness Model

The difficulties of calculating C_U severely hindered the application of Life-Cycle Cost Analysis (LCCA), hence the proposals of other methods of estimating benefits. Many researchers recommend the area under the performance condition curve as users' benefits [24-28]. The maintenance effectiveness model, which defines benefits (E) as the product of the area under the performance condition index (PCI) curve, traffic volume, and the area of pavement section, is taken from [29] as is shown in Fig. 3 and Eq. (7). It is worth noting that the uncertainties of PCI lead to the uncertainties of benefits.

$$\mathrm{E} = \sum_0^{x_S}[f_0(x) - y_0] \times AT \times AREA + \sum_0^{x_T}[f_j(x) - y_0] \times AT \times AREA \quad (7)$$

where $f_0(x)$ and $f_j(x)$ represent PCI with no maintenance measure and the measure j, respectively. When PCI decreases to y_0, the benefits baseline of PCI at the time period x_0, refurbishing will be chosen to rehabilitate the pavement. AT is annual numbers of arrivals and departures, and $Area$ is the area of the pavement section.

M&R Decision Making Model

To maintain the serviceability of the entire airport pavement network, a variety of maintenance goals are proposed, including minimizing the present worth of the total maintenance cost, maximizing the cost-effectiveness of maintenance activities, maximizing network performance, minimizing road user cost, etc., with a certain set of constraints (e.g., budget, pavement standard, manpower, equipment, etc.). In this paper, the former two goals are adopted, and a chance-constrained programming methodology is introduced to establish two models: maintenance cost minimization model and cost effectiveness maximization model.

Expected Value Model

For comparison purposes, the expected value models will be presented and followed by their chance-constrained counterparts.

Maintenance Cost Minimization

$$\min Z_0 = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\sum_{t=1}^{T} X_{i,j}(t)\tilde{C}_{A_{i,j}}(t)}{(1+\tilde{r})^t} - \frac{\sum_{i=1}^{M} C_{S_i}(T)}{(1+\tilde{r})^T} \quad (8a)$$

Subject to:

$$\widetilde{PCI}_i(t) \geq MinPCI_i \quad (\forall i, t) \quad (8b)$$

$$\sum_{j=1}^{N} X_{i,j}(t) = 1 \quad (\forall i, t) \quad (8c)$$

$$X_{i,j}(t) = \begin{cases} 1 & \text{the measure j is adopted in section i at the year t} \\ 0 & \text{else} \end{cases} \quad (8d)$$

where: $\tilde{r}$ is the discount rate, and $\mathrm{MinPCI_i}$ is the minimum acceptable PCI for section *i*.

Under this formulation, the objective functions, Eq. (8a), aim to minimize the present worth of the total maintenance cost Z_0 in analysis period (T) for the network. M represents the number of sections analyzed and N the number of measures. Eq. (8a) maintains that the performance of all pavement sections is above the mimuim accepted PCI at any year *t*. Eq. (8c) ensures that only one of N measures can be adopted for section *i* at year *t*. The variables *i*, *j*, and *t*, respectively, indicate section *i*, measure *j*, and the year *t* as is shown in Eq. (8d).

Cost Effectiveness Maximization

$$\max \bar{Z}_1 = \sum_{i=1}^{M}\left(\frac{\sum_{j=1}^{N}\sum_{t=1}^{T} X_{i,j}(t)\tilde{E}_{i,j}(t)}{\sum_{j=1}^{N}\sum_{t=1}^{T}(\tilde{C}_{A_{i,j}}(t)+\tilde{C}_{D_{i,j}}(t))/(1+\tilde{r})^t - \tilde{C}_{S_i}(T)/(1+\tilde{r})^T}\right) \quad (9a)$$

Subject to:

$$\sum_{i=1}^{M}\sum_{j=1}^{N}\sum_{t=1}^{T} X_{i,j}(t)\,\tilde{C}_{A_{i,j}}(t) \leq MaxC_A \quad (\forall i, t) \quad (9b)$$

$$\sum_{j=1}^{M} X_{i,j}(t) \leq N_j \quad (\forall t) \quad (9c)$$

In addition to the minimization of maintenance cost, decision makers often require the most cost effective plan with budget constraints. The objective function Eq. (9a) is used in this case. The cost effectiveness is defined as the ratio of maintenance effectiveness, E, and total cost *C*. Eq. (9b) ensures that the annual maintenance expenditure does not exceed the available budget. Eq. (9c) constrains the number of pavement sections maintained by the same M&R measure. Similarly, the cost minimization model considers the same set of constraints as the maintenance cost minimization model (Eqs. (8c)-(8d)).

Chance-constrained Model

In real life, existence of uncertainties makes the probability of the expected incident quite low; in other words, the incident expected is of high risk. Therefore, chance-constrained counterparts are proposed to mitigate the risk of making decisions. In this section, the uncertainties of parameters, such as $\tilde{C}_A$ (parameters with "～" are random variables), are included in the following two chance-constrained models.

Maintenance Cost Minimization

$$\min \bar{Z}_0 = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\sum_{t=1}^{T} X_{i,j}(t)\tilde{C}_{A_{i,j}}(t)}{(1+\tilde{r})^t} - \frac{\sum_{i=1}^{M} C_{S_i}(T)}{(1+\tilde{r})^T} \quad (10a)$$

Subject to:

$$P\left(\widetilde{PCI}_i(t) \geq MinPCI_i\right) \geq \alpha \ \ (\forall i, t) \quad (10b)$$

$$P(Z_0 \leq \bar{Z}_0) \geq \beta \quad (10c)$$

where: 1-α and 1-β represent the acceptable risk of not meeting the requirements of PCI and objective programming goal Z_0, respectively. In other words, the PCI of each pavement section maintained each year must satisfy the required standard ($MinPCI_i$) with a certain confidence level, α,- a chance constraint, and the objective programming goal, Z_0, with a certain confidence level, β. The next deterministic formulation can be modified to account for the uncertainties of the parameters in the same manner.

Cost Effectiveness Maximization

$$\max \bar{Z}_1 = \sum_{i=1}^{M}\left(\frac{\sum_{j=1}^{N}\sum_{t=1}^{T} X_{i,j}(t)\tilde{E}_{i,j}(t)}{\sum_{j=1}^{N}\sum_{t=1}^{T}(\tilde{C}_{A_{i,j}}(t)+\tilde{C}_{D_{i,j}}(t))/(1+\tilde{r})^t - \tilde{C}_{S_i}(T)/(1+\tilde{r})^T}\right) \quad (11a)$$

Subject to:

$$P\left(\sum_{i=1}^{M}\sum_{j=1}^{N}\sum_{t=1}^{T} X_{i,j}(t)\,\tilde{C}_{A_{i,j}}(t) \leq MaxC_A\right) \geq \alpha \quad (\forall i, t) \quad (11b)$$

$$P(Z_1 \leq \bar{Z}_1) \geq \beta \quad (11c)$$

As is shown above, these formulations include non-linear functions and integer variables. In addition, there are numerous pavement sections and feasible M&R measures. Moreover, when the stochastic elements are incorporated into the formulation, it is difficult to solve the problem with traditional optimization techniques. This contributes to the use of the MC simulation-based GA approach for solving pavement maintenance program proposed in this research.

Simulation-optimization Framework

An MC simulation-based GA approach is applied to solve the stochastic programs. MC is incorporated into the GA, which is used to obtain an optimization sequence as well as evaluate the stochastic parameters of object function and the constraints.

Chromosome Coding

One notable aspect of GA's application is the coding of the chromosome. For pavement management optimization here, the chromosome is coded as a series of T-year maintenance decisions for all pavement sections N, as is shown in Fig. 4. Also, 1 represents the adoption of refurbishing in the section this year and 0, the rejection, which means only routine maintenance activities are adopted.

Fitness Evaluation.

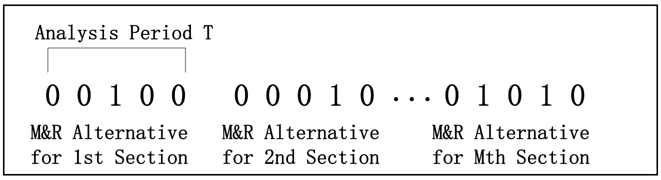

Fig. 4. Chromosome Coding.

The fitness evaluation drives the convergence to the optimization value. However, stochastic parameters prevent application of the value of objective function as the fitness evaluation. MC is adopted to solve the problem. The fitness evaluation method based on MC simulation is displayed in Fig. 5 and summarized as follows:

1. Take each sample of different parameters according to the given distribution;
2. Calculate and record the PCI values in analysis period;
3. With repeated sampling and calculating, PCI value tends to obey the distribution given in step 1;
4. Calculate the values of objective function and constraints for each PCI calculation sample;
5. Evaluate the distribution characteristics of the objective function and constraints;
6. Compare reliability, φ, obtained on the prerequisite of satisfying the constraints' limits, with the given reliability, α. If $\varphi \geq \alpha$, it is believed that individuals meet constraint requirements, and β percentile of the objective function's distribution should be exported as individual fitness. Otherwise, the individual fitness is defined as the product of β percentile of the objective function's distribution and the penalty factor λ. λ is given as shown in Eq. (12). Eq. (12) ensures that lower reliability φ contributes to lower λ, thus resulting in lower probabilities to pass to the next generation.

$$\lambda = \frac{1-\alpha}{1-\varphi} \quad (12)$$

MC Simulation-based GA Procedure

The MC simulation-based GA procedure studied here is shown in Fig. 6 and is summarized as follows:

1. Code the chromosome with M&R solutions and initiate the population;
2. Each M&R solution's fitness will be evaluated based on MC simulation;
3. Rank the M&R solutions in descending order by their fitness. Also, the former 20 solutions and their calculation results are recorded;
4. Update the solutions by GA operators, including selection, crossover, and mutation to obtain a new set of solutions;
5. Repeat steps 2, 3 and 4 until stopping criteria is met.
6. Report the optimization sequence.

Table 2. Case Study Parameters.

Analysis Period T	20 years	MinPCI	80
Annual Air Traffic	550	Discount Rate r	8%[31,32]
Traffic Annual Growth Rate	0	Reliability α, β	90%

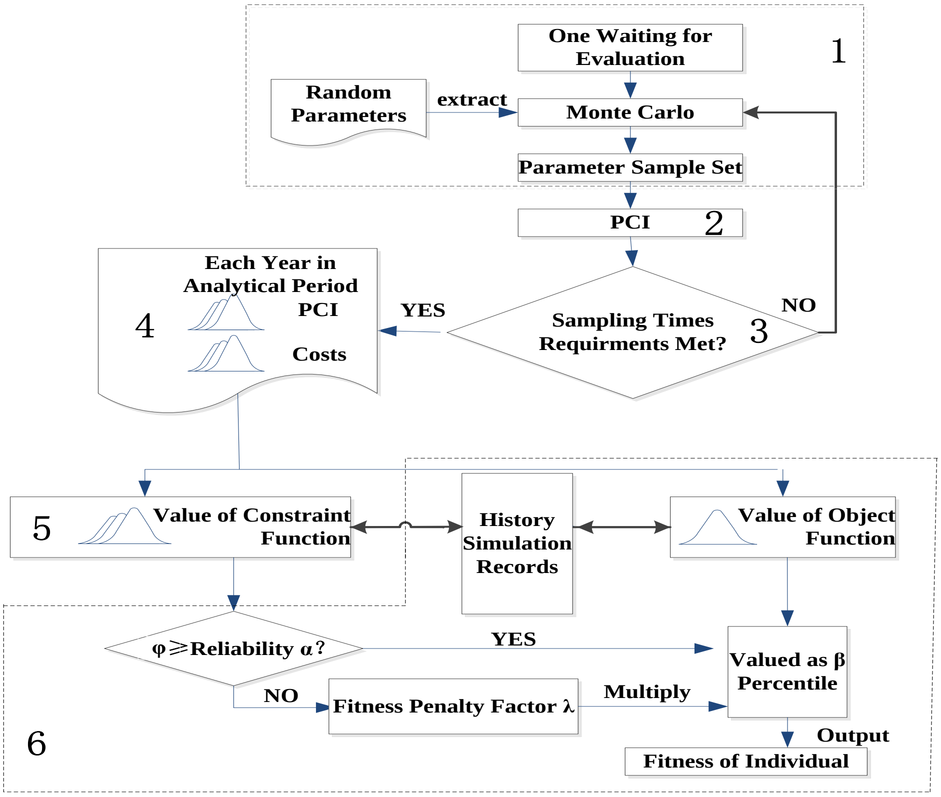

Fig. 5. Fitness Evaluation Based on Monte Carlo.

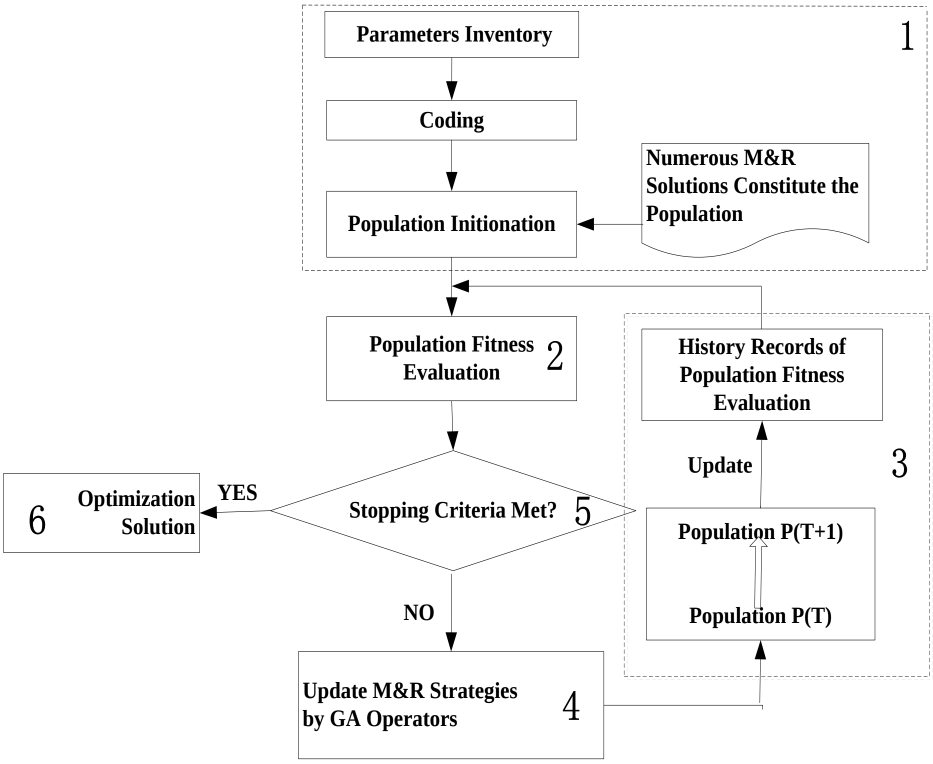

Fig. 6. Flow Diagram for MC Simulation-based GA.

Table 1. PCI Data of 1st Runway.

Year	1998	2000	2001	2002	2004	2005	2008	2009	2010
Data	100	94	90	85	80	100	97	95	90

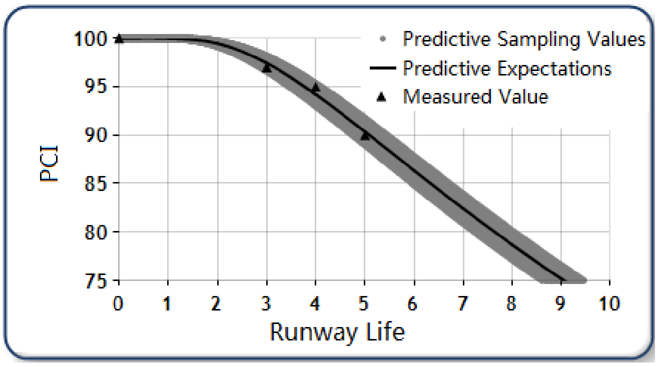

Fig. 7. PCI Prediction Values (without Considertion of Residual Error).

Case Study

General Information

In this section, an airport is studied based on the models and simulation method presented in former sections. The airport in this study, Shanghai Hongqiao International Airport, located in Shanghai, eastern China, has two runways now. The first runway has been refurbished several times with asphalt, and the second was put into operation in 2010. The runways are under high maintenance level, as defined in Eq. (2), and refurbishing is the single choice of major rehabilitation here. The airport agency has monitored the PCI conditions of the first runway by means of visual inspection performed by trained staff since 1998, and they have obtained the nine groups of data listed in Table 1. The survey assessment was performed following the guidelines provided in the Pavement Condition Rating Manual [30].

Until 2011, which was the first year analyzed, the former runway is 3.4 kilometers long and 57.6 meters wide, and its PCI value is 90. This runway‘s characteristics are simulated based on the assumed parameters and variables shown in Table 2. It is worth noting that the discount rate, r, is set as a constant even in chance-constrained models and distribution of PCI is obtained by the *Bayesian approach*[2] . The performance prediction formulation is shown in Eq. (13) and distribution of predicted PCI is displayed in Fig. 7[3].

$$PCI(t) = 100(1 - e^{-(\frac{13.12}{t})^{0.88}}) \tag{13}$$

Selection of MC Dimulation-based GA Parameters

The following settings are used for GA in this simulation: the population size is 30, crossover probability is 0.2, and the mutation probability is 0.08. Roulette selection operator is adopted to make preparation for crossover and mutation operation. Calibration of roulette is divided by each chromosome’s fitness, and the chromosome of higher fitness occupies more area on roulette, which results in higher probability of this chromosome being selected. Chromosomes are ranked in their fitness and only the top 20 chromosomes are eligible for reproduction. The genetic search will not stop until 50,000 generations are reached.

[2] The Bayesian approach applied here is under review by the 2013 IJPC-International Journal of Pavements Conference.

[3] The initial year is 2005 when the first runway had just been refurbished with asphalt overlays.

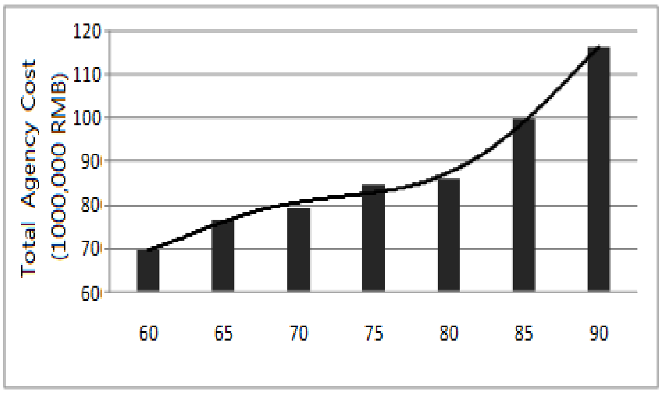

Fig. 8. C_A versus MinPCI.

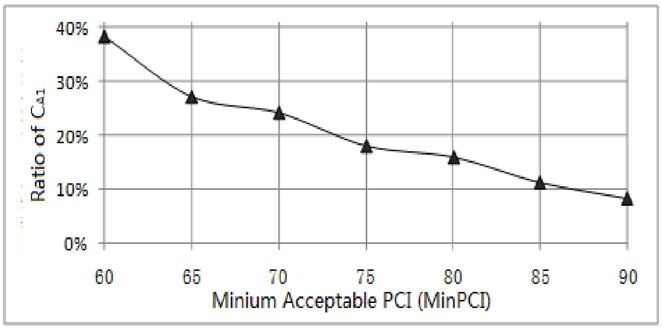

Fig. 9. Ratio of C_{A1} versus MinPCI.

Table 3. Refurbishment Timing vs. MinPCI.

Min PCI	C_A (1000 RMB)	Ratio of C_{A1}	Refurbishment Timing in Analysis Period
60	69370	38.21%	(2018)
65	76540	27.26%	(2016，2027)
70	79020	24.05%	(2015，2025)
75	84650	18.02%	(2013，2021，2029)
80	85890	15.89%	(2012，2019，2026)
85	99620	11.25%	(2011，2017，2023，2028)
90	116330	8.21%	(2011，2016，2021，2025，2029)

Results

M&R solutions were developed based on the expected value and chance-constrained formulations.

C_A versus PCI

To investigate the relationship between maintenance cost and MinPCI, a series of simulations in which MinPCI ranges from 60 to 90 in 5 intervals are applied. Fig. 8 displays the relationship between the total maintenance cost and MinPCI while Fig. 9 shows the trend that the ratio of C_{A1} varies with MinPCI. In addition, optimization refurbishment timing for different MinPCI is listed in Table 3.

As shown in Fig. 8, for asphalt overlay under the high level routine maintenance, C_A appears to have a slow growth when $MinPCI$ increases from 60 to 80, while having a rapid growth when $MinPCI$ increases from 80 to 90. Meanwhile, the number of refurbishing increases from one (MinPCI = 60) to five (MinPCI = 90), as shown in Table 3. Lower standards of MinPCI could reduce the number of refurbishing, whereas the ratio of C_{A1} appears to showsignificant growth, ranging from 8.21% to 38.12%, as shown in Fig. 9. It means that large routine maintenance work is required to ensure the safe operation of the runway and this should be a reason why there's no substantial difference in the agency cost when MinPCI increases from 60 to 80. In other words, low standard of MinPCI not only places more burden on the agency, but also threatens the safety. However, an extremely high standard of MinPCI, namely MinPCI is set at 90, will result in numbers of refurbishing, threatening flight operation, and significantly increasing maintenance costs.

Analysis for Different Reliabilities

Higher reliability usually results in higher maintenance cost. Hence, it is necessary to analyze the relationship between reliability (α and β) and maintenance cost. Totally, 9 groups of α and β values, consisting of (0.3,0.3), (0.4,0.4), (0.5,0.5), (0.6,0.6), (0.7,0.7), (0.8,0.8), (0.9,0.9), (0.95,0.95), (0.99,0.99) were analyzed, and the results are shown in Fig. 10.

The total agency cost (C_A) increases about 3.52 million RMB (559,000 U.S. dollars) for every 10 percent increase of reliability at the range of 0.3 to 0.9, and the total present value at the reliability of 0.9 is only 1.32 times that at the reliability of 0.3. However, the total cost appears to have a fast nonlinear growth when the reliability ranges from 0.9 to 0.99, and even the total present value at the reliability of 0.99 is 1.25 times that at the reliability of 0.9.

Chance-constrained Models versus Expected Value Models

Expected value models are easier to calculate, but have higher risk than chance-constrained models. However, it is unknown to us what the confidence level of expected value models is. A comparison between expected value models and chance-constrained models is proposed, and the results are displayed in Fig. 11.

Fig. 11 shows that for expected value models, in the years of 2013, 2021, and 2029, it is suggested to refurbish the pavement. Moreover, the present agency cost is approximately 67.92 million RMB. Compared to the expected value models, the chance-constrained models are of higher maintenance cost, which is 1.265 times that of expected value models, and the refurbishing-time intervals reduce from 8 years to 7 years. An interesting finding can be drawn from the comparason of two models' results. The optimization sequence of expected value models is close to that of chance-constrained models at the reliability of 0.4, and even the refurbishing timing is the same. It can be inferred that it is not reliable to adopt the result of expected value model.

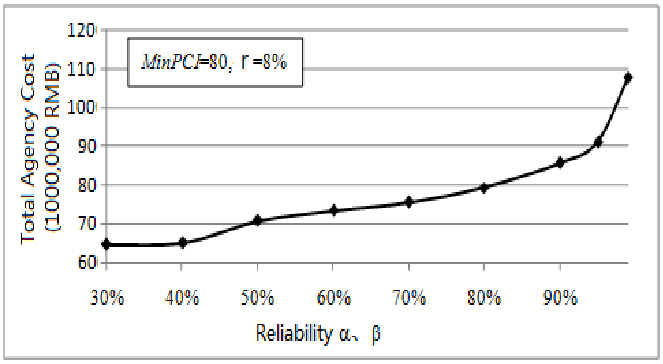

Fig. 10. Total Agency Cost versus Reliability.

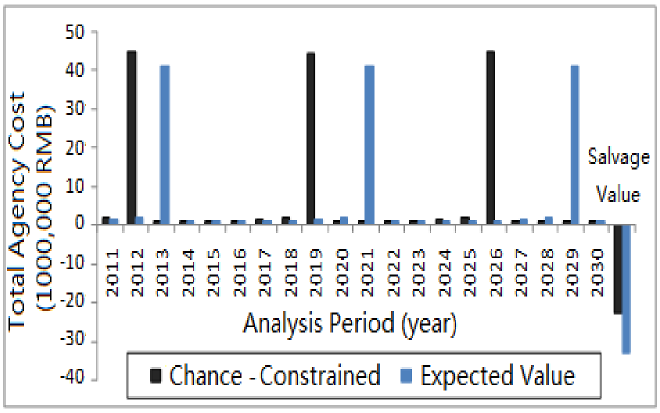

Fig. 11. Total Agency Cost Allocation under Cost Effectiveness Maximization.

Table 4. Refurbishing Timing Difference between Two Models.

Min PCI	Refurbishment Timing in Analysis Period	
	Cost Effectiveness Maximization	Maintenance Cost Minimization
60	(2012，2020，2027)	(2018)
65	(2012，2020，2027)	(2016，2027)
70	(2012，2019，2026)	(2015，2025)
75	(2012，2019，2026)	(2013，2021，2029)
80	(2012，2019，2026)	(2012，2019，2026)
84	(2012，2019，2026)	—
85	(2011，2017，2023，2028)	(2011，2017，2023，2028)
90	(2011，2017，2022，2027)	(2011，2016，2021，2025，2029)

Maintenance Cost Minimization versus Cost Effectiveness Maximization

Previous analyses in this case study aim at maintenance cost minimization for the first runway. Namely, only maintenance cost minimization models are utilized and the effects of user cost and benefits on the refurbishing plan have not been taken into consideration.

Cost effectiveness maximization models are analyzed here to compare with the results of maintenance cost minimization. It is assumed that there are no constraints of agency cost and delay cost, and other assumptions are the same as maintenance cost

Table 5. Parameters of Effectiveness Maximization Formulations.

Initiation-study Year	2011	MinPCI	Asphalt Concrete：80 Cement Concrete：80
Analysis Period	20 Years	Discount Rate (r)	8%
Air Traffic at the Initiation-study Year	630 Flights/h	Reliability α	90%
Annual Traffic-growth Rate	5%, (Less Than 900)	Reliability β	90%
Average Single Runway Volume Per Hour	40 Flights/h	Major Rehabilitation Span	3 month
Average Double Runway Volume Per Hour	55 Flights/h	Number of Major Rehabilitation Per Year	≤1
Ratio of Traffic Burdened by Per Runway	0.5	Average Delay Cost Per Aircraft	12000RMB/flight·h
Average Numbers of Passengers Per Aircraft	144	Average Delay Cost Per Passenger	150RMB/person·h

minimization models. The comparison of optimization results is shown in Table 4.

It can be concluded that for different MinPCI, cost effectiveness maximization models are more robust than maintenance cost minimization models. At the range of 70 to 84, for cost effectiveness maximization models, the refurbishing plan does not change, and is consistent with that when MinPCI is 80 for maintenance cost minimization models. When MinPCI increases from 60 to 70, optimization refurbishing plan is stable, which is totally different from that at the same MinPCI range. And when MinPCI is more than 85, the numbers of refurbishing increases, hence the change of refurbishing plan.

Delay Effects on M&R Plan

To incorporate delay effects during major rehabilitation period into M&R decision making, the two runways of the study airport are investigated based on the cost effectiveness maximization formulations. The parameters used in this study are displayed in Table 5. Here, only one runway is allowed to accept major rehabilitation, and this is the reason why the number of major rehabilitation per year in Table 5 is not more than 1. Also, it is worth noting that value of air traffic is based on the actual traffic of the study airport, and the average single and double runway volume per hour are considered to avoid the severe delay in operation.

For comparison, two situations are supposed:

1. Refurbishing will be arranged at night when the runway is closed. Therefore, it will not influence operation of this runway the next day;
2. Refurbishing is arranged during the day for one runway, and the traffic will be taken by the other runway.

Additionally, it is assumed that no difference exists between the cost of working at night and during the day, and the extra cost caused by the taxing difference between the two situations is neglected. The optimization results of the two models are displayed in Fig. 12.

Fig. 12 shows that the refurbishing timing of the first runway has been postponed for one year since the first refurbishment in 2013. Therefore it could be concluded that delay effects do influence the M&R plan. Actually, delay effects could be considered as an increase of agency cost from Eq. (11a), and this is the way of delay effects to influence the cost effectiveness, thus achieving a new balance. The calculation results show that the delay cost in this case cannot be neglected. For example, in 2021, major rehabilitation cost and the delay cost of the first runway are 42.28 million RMB and 20.79 million RMB, respectively and it is easy to calculate the ratio of them: 2.03:1.

In the subsection “User Cost Model,” the difficulties of estimating the delay cost accurately have been mentioned. This motivates the sensitivity analysis of delay cost. The delay cost is scaled by the scaling factors ranging from 0 to 4. Namely, the delay cost is taken into cost effectiveness maximization formulations only by multiplying the scaling factors. The results are displayed in Table 6.

From Table 6, it can be deduced that when below 40 percent (scaling factor ranges from 0.5 to 1.4), prediction error does not

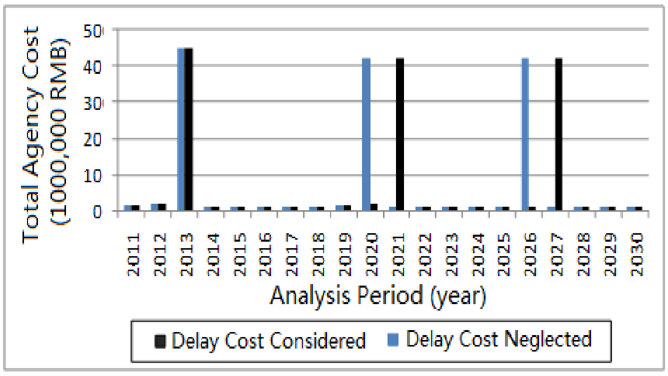

Fig. 12. Effects of Delay Cost on M&R Plan for First Runway.

Table 6. Major Rehabilitation Schedule on Different Scaling Factors.

Scaling Factors	Major Rehabilitation Schedule during Analysis Period (year)	
	1st Runway	2nd Runway
0 (Delay Cost Neglected)	(2013，2020，2026)	(2024)
0.1	(2013，2020，2026)	(2024)
0.5	(2013，2021，2027)	(2024)
0.8	(2013，2021，2027)	(2024)
1	(2013，2021，2027)	(2024)
1.2	(2013，2021，2027)	(2024)
1.4	(2013，2021，2027)	(2024)
1.5	(2013，2021，2027)	(2022)
2.0	(2013，2021，2027)	(2022)
3.0	(2012，2019，2025，2030)	No Major Rehabilitation
4.0	(2012，2019，2025，2030)	No Major Rehabilitation

have influence on the optimization maintenance result approximately. However, with an increase of the prediction error, not only is the major rehabilitation timing influenced, but the amount of major rehabilitation is influenced as well. For instance, refurbishing timing of the second runway is arranged two years ahead of the schedule when the scaling factor ranges from 1.4 to 1.5.

Summary and Conclusion

Based on the results of this study, the expected value models are confirmed unreliable. By incorporating the confidence level into the formulations, the chance-constrained models can more effectively avoid risks. In addition, delay cost does have influence on the M&R plan, and its prediction error, if confined to a certain extent, has little influence on the optimization sequence. Therefore, it can be concluded that to find maintenance and rehabilitation policies for airport pavement management, it is essential to take parameters uncertainty and delay effects into consideration.

Through the proposed approach, Monte Carlo simulation-based genetic algorithm, an airport pavement management system can develop a pavement maintenance plan based on the models presented. And this method has been evidenced feasible by the case study. The case study furthermore proves that it is reasonable for an asphalt overlay to be refurbished when the PCI ranges from 75 to 85 and 0.9 may be a beneficial option of reliability in chance-constrained formulations.

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