Expressway Maintenance Decision Model Based on Immune Genetic Algorithm

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Abstract **- Expressway maintenance is a specific and complex systems engineering. In expressway maintenance decision-making process, it is difficult to assess complex effect caused by environment changes. Moreover, different policy makers have some certain preferences so that the traditional dynamic programming algorithm is greatly limited. To solve these problems, immune genetic algorithm with diversity control is designed for multi-objective optimization of expressway maintenance. The algorithm has some unique features such as control of concentration, control of affinity, and genetic mechanisms, which will improve expressway maintenance dynamic decision. From simulation on expressway maintenance work, the integration of expressway maintenance objectives and the application of immune genetic algorithm are proven effective.**

Keywords - Expressway Maintenance; Multi-objective Optimization; Immune Genetic Algorithm; Diversity Control

I. INTRODUCTION

The concept of pavement performance is first proposed in the early 1960s. As the results of the expressway strategic research program (SHRP) shows, for a qualified road, there is 40% drop in performance in 75% of the life time. This phase is called preventive maintenance phase. If not maintained timely, its performance once again will fall by 40% in later 12% life time, and the maintenance cost will increase by 3~10 times[1].For expressway pavement, pavement performance refers to have the ability to drive vehicles with safety, high speed, comfort and economy in its life cycle. Pavement performance is the most fundamental basis for pavement performance evaluation, performance prediction and selecting pavement maintenance optimization plan. In general, the use of pavement performance can be divided into five aspects: functional performance, structure performance, structure bearing performance, and appearance performance. From the point of the development model of road management and maintenance, government agencies mostly are in charge of road management abroad, and implementation of specific and professional maintenance engineering work is basically undertook by the professional maintenance contractors ,realizing the real separation of management and maintenance.Over the years, the management of road maintenance and conservation of the contractor regarded ‘smooth, clean, green, beauty, security’ as ‘five majors’ and the highest conduct code of road management and maintenance, which hasn’t returned to the path of claiming benefit on road.

At present, various countries have established a pavement management system that involves the system construction, maintenance planning, cost optimization, etc. AASHTO (American Association of State Expressway and Transportation Officials) have established PSI (Present Service ability Index) pavement evaluation model through pavement experiment. T. F. Fwa[2]. studied on the multi-objective optimization problem of the network level pavement maintenance planning. Medury and Madanat [3,4] worked on the method of calculating expected costs with random strategy. In the respect of Pavement maintenance management decision-making, it develops from aggregation and heuristic two directions. The former focuses on the centralized optimization of problem while the latter focuses on the idea of successive approximation. With the expansion and application of Image technology, Internet, Cloud Computing technology and Internet of things technology, the application performance of pavement management system is further improved. However, there still exists a variety of constraints on the system management complexity, mechanical property of expressway’s section, maintenance planning and road network structure, etc, which make it difficult to reconcile all the objectives. The expressway maintenance multi-objective is aimed to be optimized by using the Immune genetic algorithm and combining decision preference function.

II. MULTI-OBJECTIVE OPTIMIZATION PROBLEM OF EXPRESSWAY MAINTENANCE

Expressway managers need to consider a number of factors when selecting maintenance plans, who should comprehensively consider the technical index and operation of micro index, sections importance and economic effect of meso, and social impact of macro. In combination with the experts' experience, plans for the maintenance of the road will be worked out. Large and medium repairing engineering especially requires professional and strict foreign bidding and bidding program.

In project management, the ideal goal of what project managers expect is that short duration, low cost and high quality can be satisfied simultaneously. However, because the mutual connection and restriction of the three targets, other targets will inevitably be harmed while meeting an optimal target. Therefore, how to achieve a balanced optimization among duration, cost and quality becomes a hot spot in the field of engineering project management. Babu[5], etc. first proposed three linear programming model to study the correlation among duration, cost and quality; Ziarati [6] studied the resource-constrained project planning problem under determination environment. Zhang Lianying[7] proposed quality model based on Network Reliability, thereby improving duration-cost-quality tradeoff optimization problem of the three; Azaron[8] established a duration, cost, and quality balanced multi-objective optimization model under random PERT environment; Ke[9]established three kinds of duration, cost, quality tradeoff optimization model to meet the management objectives of different decision-makers.

Pavement existing service performance index PSI (Present Service ability Index) rating by road is mainly a combination of detection basic data and expert experience score up, and then on the basis of the measured data regression analysis, establishing a relationship between PSI and road conditions. PSI is a dimensionless quantity, reflecting the average level of road quality and service, its value ranging from1 to 5. PSI includes such influencing factors as pavement roughness, rutting and pavement damage, of which the most attention is the impact of pavement roughness, indicating PSI pays more attention to the road quality and service from road user's perspective. US AASHO established a PSI equation, and many countries have established their own PSI equation, but the focuses vary. US PSI equation is as follows.

$$PSI = 5.03 - 1.91g(1+SV) - 0.01\sqrt{C+P} - 0.21RD^2 \tag{1}$$

SV is average gradient change. C is the area of pavement cracks. P is the repair area. RD is the average rut depth. The equation reflects the degree of road quality and service levels mainly through the pavement roughness. Japan PSI equation is as follows.

$$PSI = 4.53 - 0.5181g\delta - \sqrt{C} - 0.0017RD^2 \tag{2}$$

δ is a longitudinal flatness standard deviation. C is the crack ratio. RD for the average rut depth. Japan's evaluation model pays more emphasis on impact of pavement damage (cracks) and rutting.

PSI equation is established on the basis of road test evaluation group evaluation, and has strong timeliness restrictions. The combined statistics of driving performance and surface damage has certain bias. Road test technology and equipment as well as criteria for evaluating have been certain updated.

In addition to PSI, each country has also established index of characteristics, such as conservation and management index MCI (Maintenance Control Index), pavement condition index PCI (Pavement Condition Index), general pavement crack index UCI (Universal Crack Index). MCI established a non-linear relationship between MCI and the influencing factors of pavement cracks, pavement roughness, and rutting, mainly through the multiple regression analysis. For pavement damage condition, PCI uses deducting score method to establish a kind of pavement performance evaluation index. UCI mainly targeted pavement cracks.

‘China Expressway Asphalt Pavement Performance Evaluation Standard’ has made provisions on asphalt pavement performance, including sub-evaluation and comprehensive evaluation. For high-speed road pavement characteristics and common diseases, it establishes a corresponding set of pavement performance evaluation, namely expressway pavement maintenance quality index EPQI (Expressway Pavement quality index).

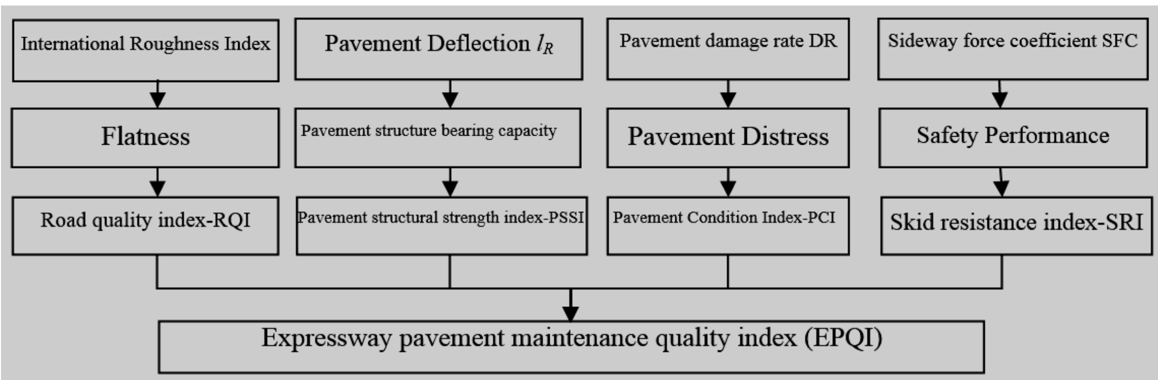

Fig. (1). EPQI Index Structure

The current expressway management department has basically established a pavement evaluation system. There is pavement evaluation model base in the system. It mainly refers to the basic model of "Expressway technical condition evaluation criteria" and makes adaptive improvement design combining with actual situation.

III. MULTI-OBJECTIVE OPTIMIZATION OF EXPRESSWAY MAINTENANCE

Pavement Maintenance Decision is actually a combination of nonlinear multi-objective optimization problem. Many scholars use the evolutionary algorithm to plan or solve this kind of problem. Evolutionary algorithm search is random and is a natural evolution simulation algorithm. With respect to the conventional algorithm, evolutionary algorithm does not require strict mathematical constraints. Evolutionary algorithm has pleiotropy and overall importance when it searches Pareto. To solve the dynamic multi-objective optimization (DMO), scholars have developed several sets of multi-objective optimization evolutionary algorithms, such as MOGA[10], NPGA[11], SPEA[12], PAES[13], NSGA[14], PSO[15], IA[16]. Shang Ronghua [17] introduces immune clone algorithm into multi-objective optimization problem. When solving multi-objective optimization problem, each time a certain number of non-dominated solutions will be selected into the next generation optimization. Through clonal selection policy good diversity and convergence will be maintained. Among the methods of object- oriented design process modeling, the multi-objective optimization[18] and the design space search [20] are current hot topic. At present, there is no conclusive agreement on selecting pavement performance evaluation indicator. Different countries and regions have different indicators, mainly RQI, PCI, but they can not reflect the full information. For example, PCI is only a kind of appearance evaluation of pavement condition, and different damage conditions of the road may have the same PCI value. Normally, we can set a specific index for roads and establish performance evaluation index system combined with routine indicators. Therefore, it can reflect more comprehensive information as well as trace main problems, select multiple individual index, combine with comprehensive index, and comprehensively evaluate condition of pavement that need to be maintained.

In China's expressway asphalt pavement surface distress, ruts and cracks account for 70% to 90% in pavement damage, while other types of damage such as pits, pro package, waves, local subsidence, oil spillage are less than 20%. Once expressways being found relatively serious disease, maintenance departments must take certain measures to deal with. According to pavement maintenance management decision-making, they choose five specific maintenance measures: routine maintenance and minor repairs, repair overlay, repair skid overlay layer, overhaul reconstruction, and big strong repair to maintenance asphalt pavement. Maintenance decision is a kind of NP (Non-Deterministic Polynomial, non-deterministic polynomial) problem. Evolutionary algorithm based on dynamic multi-objective optimization model can properly solve such problems.

This paper considers expressway maintenance decisions from the aspects of quality, duration and cost dimensions. Multi-objective function system is as follows.

$$\min T = [\sum_{(i,j)\in L_m} t_{ij}] \tag{3}$$

$$\min C = \sum_{(i,j)\in R} [c_{ij}^n + \alpha_{ij}(t_{ij}^n - t_{ij})^2 + c_{ij}^{in} - \frac{c_{ij}^{in} - c_{ij}^{is}}{t_{ij}^n - t_{ij}^s}(t_{ij}^n - t_{ij})] \tag{4}$$

$$\begin{aligned}\max Q = {} & (\frac{100}{1+0.0185e^{0.437IRI}}) + (100 - 15DR^{0.41}) \\ & + (\frac{100 - SRI_{\min}}{1+266e^{-0.319SFC}} + SRI_{\min}) + (\frac{100}{1+15.7e^{-5.19 l_R/l_0}})\end{aligned} \tag{5}$$

In above equations,t_{ij} means the duration between adjacent steps. $c^n{}_{ij}$ is direct cost. $c^i{}_{ij}$ is indirect cost. $t^n{}_{ij}$ is continuous duration. $t^s{}_{ij}$ is possible minimum duration. $c^{in}{}_{ij}$ and $c^{is}{}_{ij}$ are corresponding indirect cost. IRI□[1.4,1.5], the unit is m/km, SFC□[40,50], DR□[0.001,0.0015],l_R, l_0□[0.01,0.012],the unit is mm. α_{ij} is a marginal increase factor,□(0,1).

IV. IMMUNE GENETIC ALGORITHM FOR MULTI-OBJECTIVE OPTIMIZATION

The traditional method to solve the maintenance decision optimization problem is mathematical programming method, including linear programming, nonlinear programming and dynamic programming. Though the satisfactory solution can be worked out, there exist dual defects: one is the instability of the solution, which means the optimization strategy may change a lot when the fund budget of expressway maintenance varies slightly. The other is that, the calculation speed of mathematical programming is much slow with large decision space. The genetic algorithm based on the natural selection and genetic principles handles complicated optimization problems efficiently and excellently. The evolutionary algorithm typically like representative of the genetic algorithm produced in the 1970s now has been widely used in various fields for global optimization problems, such as structural design and transportation, as well as some related applications to expressway maintenance decision optimization.

Poor local searching and premature convergence limit the standard genetic algorithm to solve multi-objective optimization problems. Therefore, the scholars put forward various improved algorithm on multi-objective optimization, such as Niche Genetic Algorithm, Adaptive Chaos Particle Swarm Optimization Algorithm (ACPSO) , Immune chaos network, Compact Genetic Algorithm[21,22], Baldwin adaptive algorithm. These algorithms have enhanced performance mainly by improving the convergence speed and the diversity of population control.

Immune algorithm mainly contains immune operations like cloning selection, network distribution, negative selection, learning mechanism, memory mechanism, concentration control, and vaccination, which are equipped with the characters of population diversity maintenance, learning and memory accelerating convergence, parallel search, etc. In order to solve the conflict between population diversity and convergence, the scholars combined the immune algorithm and genetic algorithm and developed various immune genetic algorithms, which have been widely used in the engineering field [23]. Typically, De Castro designed an immune clonal selection algorithm [24] and a multi-modal function optimization algorithm based on immune network (Opt-aiNet) . The parameters of immune genetic algorithm influence optimization effect, in which the adaptive adjustment from crossover probability and mutation probability is an effective way to improve the algorithm convergence, but the existing immune genetic algorithms lack of adaptive control with diversity and cycle. So, according to the characteristics of diversity and distribution of population and gradual change by cycle, the cross function based on similarity and mutation function based on diversity are constructed. In the process of search, global and local information are taken into consideration simultaneously, so as to avoid the premature convergence.

The immune genetic algorithm combines the characteristics of the immune system with genetic algorithm efficiently, in which the problem to be solved is regarded as the antigen and the solution is regarded as the antibody, the approximation level between the feasible solution and the optimal solution is described as the affinity of antigen and antibody. The improved adaptive immune genetic algorithm is designed mainly based on the affinity, similarity, concentration and cycle, etc.

A. Diversity Concentration

Information entropy is an indicator of measuring similarity between antibodies. Suppose N antibodies with each M gene. Each gene has optional S symbols. The information entropy H(N) of N antibodies as follows:

$$H(N)=\frac{1}{M}\sum_{i=1}^{M}H_i(N) \quad H_i(N)=\sum_{j=1}^{S}-p_{ij}\ln p_{ij} \tag{6}$$

H_i(N) is information entropy of *ith* gene of antibody, p_{ij} is probability of a particular symbol in S symbols of *ith* gene of antibody. Antibody affinity indicates the similarity between two antibodies. The similarity between *v* antibody and *w* antibody describes as follows:

$$a_{v,w}=\frac{1}{1+H(2)} \tag{7}$$

H(2) is the information entropy between two antibodies. When *H*(2) equals to zero, it shows all genes of two antibodies are the same. $a_{v,w}$ ranges of [0, 1]. Considering the overall diversity, using information entropy as the similarity index reflects the similarity more comprehensively than using hamming distance. Antibody concentration is used to represent the number of similar antibodies scale.

$$c_v=\frac{1}{N}\sum_{w=1}^{N}b_{v,w}\,,b_{v,w}=\begin{cases}1,\alpha a_v\le a_w\le\beta a_v\\ \quad 0\end{cases} \tag{8}$$

α and β are the adjustment parameter, $\alpha<1<\beta$. Due to $\alpha<1<\beta$, concentration can be limited to a range for Baldwin effect between antibodies, which will appropriately encourage better antibodies.

B. Memory Selection

The immune selection operation chooses optimal antibody in immune space which guarantees the convergence. The selection probability of immune algorithm contains antibody affinity and concentration, which simulates concentration regulation mechanism of biological immune system. The selection probability (p_v) of antibody *v* is controlled by the affinity and the concentration, which is positive relationship with affinity and inverse relationship with concentration.

$$p_v=\sqrt{\frac{a_v}{\sum_{w=1}^{N}a_w}\Big/\frac{c_v}{\sum_{w=1}^{N}c_w}} \tag{9}$$

While concentration of antibody is certain, selection probability of antibody is positive to affinity. While affinity of antibody is certain, selection probability of antibody is negative to affinity. Selected antibodies are conserved in memory cells. Superior antibody replaces antibody with low affinity in memory cells, so as to update the memory unit.

C. Crossover and Mutation Operation

In immune algorithm, crossover probability and mutation probability determine performance of immune algorithm in a great extent. The generation of new antibodies speeds up when both crossover probability and mutation probability grow. Though diversity of antibody population maintain, it is easy to break the original good genes. Excessive probability even leads to random search. Too small probability is not conducive to generate new antibodies which will slow down search speed.

When diversity of antibody population is proper, the crossover and mutation operation should be reduced. While when diversity is inaptitude, the crossover and mutation operation should be increased. The interaction between the several peaks in the crossover operation should be avoided to protect the convergence direction. A more smooth way to avoid the intersection of multi-modal optimal values without setting up constant distance threshold is constructed. It is an adaptive process. After the sort from selection operation, the crossover probabilities of two adjacent antibody $q_{v,w}^{c}$ are as follows:

$$q_{v,w}^{c} = e^{\sqrt{a_{v,w}\cdot(a_v+a_w)/2}}\,\frac{1}{1+t/T} \tag{10}$$

Parameter t is evolution cycle. T is the total evolution cycle. When antibody similarity $a_{v,w}$, affinity av and aw is large, the crossover probabilities of two antibodies increase. But the crossover probability decreases with t increases. It is a comprehensive consideration of similarity and affinity, which can improve extracting the superior antibodies. The mutation probability q^m is a consistent variable, to control the overall diversity.

$$q^{m} = \lambda\cdot\sin\left(\frac{\pi}{2}\cdot e^{-H(N)}\cdot\frac{1}{1+t/T}\right) \tag{11}$$

λ is an adjustment parameter. When individual affinity tends to converge in population, ($H(N)$ is small), it is appropriate to improve the mutation probability, which is conducive to jump out of local optimum.

D. Coding Scheme

The algorithm adopts binary encoding, wherein the parameter is binary bit string in the length of L and is represented as $m = (m_1, m_2, \ldots m_L)_2$. m = 0 or 1. The real value corresponding to it is as follows.

$$x = \left(\sum_{i=0}^{L} m_i 2^i\right)\cdot\frac{x_{\max}-x_{\min}}{2^L-1}+x_{\min} \tag{12}$$

X is the parameter. [x_{max}, x_{min}] is the value range. The expressway maintenance chromosome coding structure is as follows:

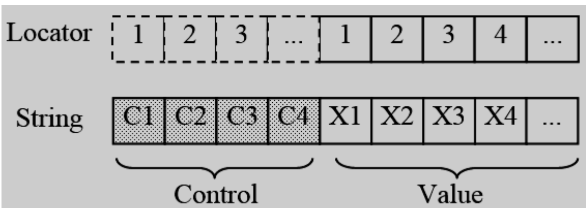

Fig. (2). Expressway Maintenance Chromosome Coding Structure
4.5 Multi-objective Function Process

Ordinarily, there are two ways of constraint condition process: constraint deviation value method and constraint deviation method.

$$C(x) = \sum_{j=1}^{q} w_j \frac{c_j(x)}{\max c_j(x)},\quad c_j(x) = \begin{cases} \max(0, g_j(x)) \\ \max(0, |h_j(x)| - \varepsilon) \end{cases} \tag{13}$$

Thereinto, C(x) is the constraint deviation value of individual x. $c_j(x)$ is the jth constraint deviation value. W_j is the weighted value of the jth constraint function. Usually, $w_j=1/q$. $g_i(\mathbf{x})\leq 0$ (i=1,…,q) is the ith inequality constraint, $h_j(\mathbf{x})=0$ (j=q+1,…,m) is the jth equality constraint.

There are two processing methods for constraint deviation value: add the constraint deviation value to the objective function of each individual so as to simplify the constraint multi-objective optimization problem into the non-constraint multi-objective optimization problem; treat the constraint deviation value as one-dimensional objective function value so as to add one dimension on the objective function, and then have the new objective function space non-constraint multi-objective optimized.

Since the genetic operator operating chromosome often generates infeasible offspring such as discrete distribution and constraint range, etc. Gen and Cheng built up adaptive penalty function to process infeasible individual. Given a individual x in the current population $p(t)$, the adaptive penalty function is as follows:

$$penalty(x) = 1 - \frac{1}{m}\sum_{i=1}^{m}\left(\frac{\Delta b_i(x)}{\Delta b_i^{\max}}\right)^{\alpha} \tag{14}$$

$$\Delta b_i(x) = \max\{0, g_i(x) - b_i\},$$

$$\text{while } \Delta b_i^{\max} = \max\{\varepsilon, \Delta b_i(x) \mid x \in p(t)\} \tag{15}$$

Thereinto, $b(x)$ denotes the variable in objective function. $g_i(x)$ is corresponding constraint. ε is a minimal constant for avoiding zero assignment. Generally, the penalty function is used in the constraint design. Transform the constraint condition into penalty function and then combine the penalty function with fitness function, so as to make the fitness function value of individual which does not satisfy the constraint condition less than that of individual which does meet the constraint condition. Finally realize the elimination of individual that does not meet the constraint condition through the survival of the fittest in algorithm.

Integrate the penalty function and fitness function. The initial fitness function minus the penalty function will get the new fitness function with constraint condition in order to solve maximization problem. While the initial fitness function plus the penalty function is required to solve the minimization problem.

V. EMPIRICAL ANALYSIS

According to the sustainable development requirement in the pavement life cycle, the service level and pavement performance are not allowed to decline severely. That means, the status in previous year offers a great reference when the decision-maker makes the current plans for the maintenance optimization. Besides, the maintenance optimization objective in the current year generally is not less than that of the previous year in the same period.

This paper empirically analyzes a certain expressway maintenance project, generates a set of multi-objective functions based on the maintenance planning, fund budget planning, project management and technical program, transforms expressway maintenance multi-objective constraint optimization function into single objective function, sets ideal solution and solves it by Matlab. The calculation results are as follows:

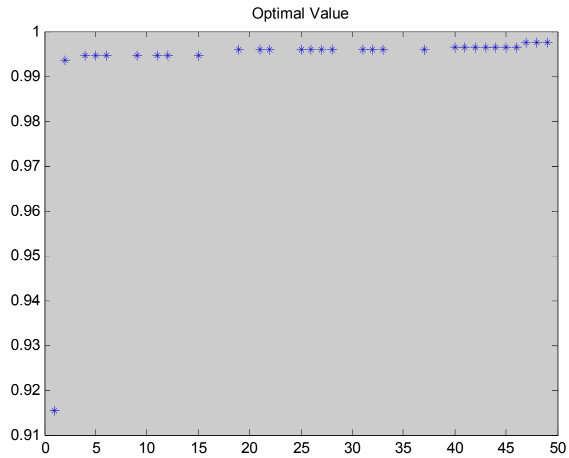

Fig. (3). Expressway Maintenance 'Duration-Cost-Quality' Objective Value Evolution

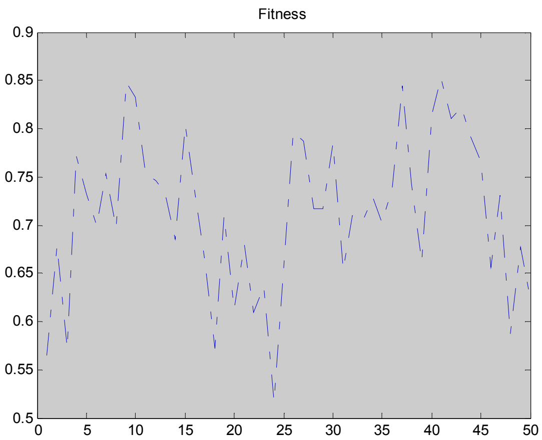

Fig.(4). Expressway Maintenance 'Duration-Cost-Quality' Fitness Evolution

From the graphs above, the effectiveness of expressway maintenance decision can achieve optimal objective value with small fluctuation. The average value of the optimal value is 0.97904, the variance is 0.000435, the average cycle of the optimal value takes 40.6. In fig 4, it shows that appropriate diversity help convergence.

-VI. CONCLUSION

The expressway maintenance work is of strong systematicness. The project construction is involved various respects and aggregated a number of technical and control indicator. This paper integrated the expressway maintenance decision objective, which can transform objectives and constraints into normal dynamic multi-objective optimization. For expressway maintenance work, this paper established expressway maintenance duration-cost-quality multi-objective decision optimization model with immune genetic algorithm, which includes expressway maintenance multi-objective function, expressway maintenance decision simulation. This work helps overcome the difficulty of balancing three optimization objectives.

CONFLICT OF INTEREST

The authors confirm that this article content has no conflicts of interest.

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