Incorporating Decision Makers' Attitudes towards Risk and Opportunity into Network-level Pavement Maintenance Optimization

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Decision makers have different attitudes towards risks and opportunities of maintenance and rehabilitation (M&R) strategies. However, most existing pavement management studies simply assumed the neutral attitudes of decision makers. The available risk-based network-level M&R optimization research equated risk with uncertainty which is actually different. Hence, this study aims to develop a method to quantitatively incorporate decision makers' attitudes towards risk and opportunity into network-level pavement maintenance planning. Quantitative criteria were developed and incorporated into the maintenance optimization model. A multi-objective optimization (MOO) model was established to explore the trade-offs between expected returns, risks, and opportunities. The proposed methods were applied to a real-world highway network as a demonstration. The results show that budget increases can simultaneously reduce expected total costs and downside risks and increase upside potential by up to 0.41%, 5.26%, and 0.92%, respectively, for each 1% increase in current year's budget, but their marginal effects are diminishing. Risk reduction requires compromising the expected performance and upside potential of the M&R strategy. The solutions derived from the mean-semivariance model dominate those from the mean-variance model. The outcomes of this study provide decision-makers with ways to incorporate their attitudes into maintenance optimization, thereby reducing risk exposure and exploiting potential opportunities.

Keywords: Decision makers' attitudes, Risk and opportunity, Pavement maintenance, Network-level optimization, Multi-objective optimization.

1 Introduction

Pavement system is an essential part of transportation infrastructure, providing a smooth and comfortable ride for road users and ensuring accessibility to a range of places. Under repeated traffic and climate effects, pavement inevitably deteriorates over time and therefore requires significant capital and natural resources to maintain it at an acceptable level of service. However, inadequate funding or natural resources is a common problem facing the transportation department in many regions. This poses a significant challenge for decision makers to more efficiently use and allocate limited funds and natural resources to maintain pavement serviceability. To address this issue, a substantial body of research on pavement maintenance and rehabilitation (M&R) optimization and budget allocation has been conducted. These studies typically formulate the M&R decision-making problem in a top-down, two-stage bottom-up (TSBU) or simultaneous network optimization (SNO) framework (Medury and Madanat, 2014). The top-down approach divides the pavement network into several groups and applies the same randomized M&R policy to segments within each group (Golabi *et al.*, 1982; Madanat *et al.*, 2006; Gao *et al.*, 2012). Though computationally efficient, it ignores the segment-specific characteristics and thereby cannot capture the heterogenous nature of pavement segments (Guo *et al.*, 2020). The SNO approach selects the optimal segment-level strategy and solves the network-level resource allocation problem simultaneously (Wang *et al.*, 2003; Medury and Madanat, 2014; Cao *et al.*, 2020). Although it can consider the interdependences among pavement segments, the complexity of the M&R optimization problem grows exponentially with the pavement network size and planning horizon length, which makes it computationally intractable or only applicable to small-scale or simplified problems.

As a compromise, the TSBU model not only accounts for segment heterogeneity but is also computationally manageable. Thus, it has been widely applied for dealing with large-scale M&R decision-making problems (Yeo *et al.*, 2013; Lee and Madanat, 2015; Swei *et al.*, 2019; Xiao *et al.*, 2021; Guo *et al.*, 2021). As the name implies, it decomposes the problem into two stages. The segment-optimal M&R activities are selected at the segment level, which are then evaluated at the network level to produce the system-optimal M&R strategy that optimizes the system-wide objectives while meeting resource constraints. Optimization goals typically include maximizing pavement performance (Swei *et al.*, 2019), maintenance cost-effectiveness (Yao *et al.*, 2020; Xiao *et al.*, 2021), or minimizing costs (agency costs or/and user costs) (Yeo *et al.*, 2013; Guo *et al.*, 2020), environmental impacts (Renard *et al.*, 2021; Shani *et al.*, 2021). Both segment- and network-level optimization problems can be solved by either mathematical programming (e.g., integer programming (IP)) (Sathaye & Madanat, 2011; Guo *et al.*, 2020) or heuristic methods (e.g., genetic algorithm (GA)) or a combination of both (Lee and Madanat, 2015; Yeo *et al.*, 2013; Zhang *et al.*, 2017). The segment level focuses on optimizing long-term objectives for individual pavement segments while the network level aims to address resource allocation issues for the entire road network.

The limitations of the existing segment-level M&R optimization models in the TSBU framework have been discussed in the authors' previous study (Yao *et al.*, 2022). At the network-level, one challenge associated with resource allocation is the explicit consideration of uncertainty (Guo *et al.*, 2020), which may cause the outcomes of decisions to be different from expected. For example, if a budget allocation scheme selects a combination of M&R activities with high expected returns but also high variability, it is very likely that the expected returns cannot be achieved when considering its uncertain nature. The main sources of uncertainty frequently mentioned in pavement management studies include pavement deterioration, M&R cost, traffic condition, budget, etc. Although many individual components of PMSs have accounted for these uncertainties by developing probabilistic models, such as probabilistic life cycle cost analysis (LCCA), life cycle assessment (LCA), and pavement performance models, they were rarely explicitly incorporated into network-level optimization. Moreover, it is noteworthy that uncertainty needs to be strictly controlled only when it could lead to undesirable consequences. If the effect of uncertainty is positive, such that higher uncertainty results in an increased probability of generating higher-than-expected returns, then such uncertainty is even preferred by decision makers. This means that uncertainty does not always equate to risk, and that the decision-making process needs to focus more on the control of risk.

Table 1 Existing studies on risk-based network-level pavement maintenance optimization.

Studies	No. of segments	Optimization objectives	Algorithms/ methods	Risk sources					Measures of risk	Methods for incorporating risks into optimization
				Pavement deterioration	M&R costs	Traffic conditions	Budgets	Others [a]		
Wu and Flintsch, 2009	/	Max. network condition, Min. total costs	Weighted sum multi-objective optimization				√		Probability of budget overrun	Chance constraint
Li and Madanu, 2009	7380	Max. total life cycle benefits	stochastic optimization		√	√	√	√	SD	MCs, stochastic optimization
Seyedshohadaie *et al.*, 2010	20	Min. the largest or sum of CVaR	LP	√					CVaR	Serving as the optimization goal
Ng *et al.*, 2011	351	Min. M&R costs	IP	√				√	Probability [b]	Chance constraint
Zhou *et al.*, 2014	672	Max. overall benefits	Simplex, heuristic		√	√		√	Sum of covariance	Markowitz model, chance constraint
Saha and Ksaibati, 2015	17	Max. PSI, Min. risk	GRG					√	Designated based on treatment costs	Serving as part of the optimization goal
Menendez and Gharaibeh, 2017	80-399	Max. benefit-cost ratio	IP	√	√		√	√	Probability [b]	MCs
Swei *et al.*, 2019	3000	Min. TWR	Knapsack approach	√	√				Budget difference	MCs
Alberti and Fiori, 2019	/	Max. the reduction of risk/cost ratio	Self-designed decision-making tool					√	Consequence multiplied by probability	Serving as part of the optimization goal
Guo *et al.*, 2020	30	Min. total costs and SD	IP	√	√				SD	MCs, Markowitz model
García-Segura *et al.*, 2020	15	Min. LCC, Max. user benefit, Min. SD of LCC	Multi-objective harmony search	√					SD	Serving as part of the optimization goal
Rashedi *et al.*, 2020	2400	Max. network performance	/			√		√	Risk index	Introducing risk tolerance constraint
Xiao *et al.*, 2021	455	Max. benefit-cost ratio, Min. risk	GA	√					SD	MCs, Markowitz model

Note: [a] e.g., discount rate, current pavement condition, effectiveness of M&R, etc.; [b] Probability of not meeting the prescribed performance requirements; LP= linear programming; CVaR= Conditional Value at Risk; MCs= Monte Carlo simulation; PSI= pavement service index; GRG= generalized reduced gradient nonlinear algorithm; TWR= traffic-weighted roughness; LCC= life cycle cost.

Table 1 summarizes the existing studies on risk-based network-level pavement maintenance optimization in terms of risk sources, risk measures, methods for incorporating risks into optimization, etc. Note that in Table 1, only studies that can provide segment-specific M&R strategies are included as they are more promising in real-world PMSs. Some studies measured the risk of M&R decisions as the probability of failing to meet prescribed performance requirements (Ng *et al.*, 2011; Menendez and Gharaibeh, 2017) or the probability of budget overruns (Wu and Flintsch, 2009) and limited the risk through methods such as chance-constraint. While these approaches have considered the likelihood of bad events, they ignored their consequences, such as the extent to which the required performance is not met or the amount of budget overruns. Other studies used standard deviation (SD) to measure the risk (Guo *et al.*, 2020; Li and Madanu, 2009; García-Segura *et al.*, 2020; Xiao *et al.*, 2021) and integrated it into the optimization model by including it as part of the optimization objective. The Markowitz model (Markowitz, 1952), also known as the mean-variance model, which originated in finance, has been used in several pavement studies to balance the expected performance and the uncertainty of M&R strategies (Guo *et al.*, 2020; Zhou *et al.*, 2014; Xiao *et al.*, 2021). However, this method considers risk as the deviation from the expected return and penalizes the upside (uncertainty in gains) and downside (uncertainty in losses) deviations equally. Thus, it has been often criticized by researchers from various disciplines (Santos *et al.*, 2017; Karacabey, 2007).

Most existing studies that aimed to optimize the expected returns while ignoring the uncertainty associated with them actually assumed that decision makers maintained a neutral attitude towards downside risks and upside potential (opportunities). The risk and opportunity attitudes of decision makers generally represent their preferences for specific situations involving uncertainty that could have positive or negative effects on objectives (Hillson and Murray-Webster, 2004; Qazi *et al.*, 2021). Risk-averse decision makers prefer to avoid uncertainty with negative effects whereas opportunity-seeking decision makers are inclined to pursue uncertainty with positive effects. Different decision makers generally have varying risk and opportunity attitudes which is among the many factors affecting the selection of strategies. Meanwhile, assessing and selecting strategies under uncertainty necessitate the incorporation of decision makers' attitudes into the decision criterion (Santos *et al.*, 2017), as the presence of uncertainty may lead to results that deviate from decision makers' expectations. Ignoring the influence of risk attitude has also been reported to result in the neglect of critical risks and be detrimental to the control of project risks (Qazi *et al.*, 2021).

Decision makers' attitudes were usually measured by different scales of numerical scores obtained through surveys and interviews of individuals of interest (Charness *et al.*, 2021). In the field of pavement management, the few attempts to measure the risk attitude of decision makers are Guo *et al.* (2020) and Xiao *et al.* (2021). They used the risk-aversion coefficient in the mean-variance model to represent decision makers' risk attitudes and minimized the risk in a network-level optimization model. However, as mentioned earlier, the mean-variance model cannot distinguish between downside and upside deviations that play completely different roles in the decision-making process. It considers the risk of deviating from the expected value rather than the risk of getting bad results such as higher LCCs than expected. Furthermore, none of the previous network-level pavement maintenance optimization models, to the best of the authors' knowledge, have taken decision makers' attitudes towards opportunities into consideration. There is also a lack of investigation into the quantitative relationship between expected returns, risks, and opportunities of M&R strategies, such as how much expected returns and opportunities need to be sacrificed in order to reduce risk.

Therefore, this study aims to develop a method to quantitatively incorporate decision makers' attitudes into pavement maintenance planning, thus enabling the control of undesirable risks and the pursuit of potential opportunities to varying degrees. To this end, quantitative criteria to measure the risks and opportunities involved in M&R strategies as well as decision makers' attitudes towards them were developed. They were also embedded into the network-level optimization model to investigate the effects of decision makers' attitudes on M&R decisions and to quantify the interrelationships between expected returns, risks, and opportunities of M&R strategies.

2 Methodology

To incorporate decision makers' attitudes towards risk and opportunity into network-level maintenance optimization, the segment-level optimization model is introduced first, which identifies two optimal M&R treatment alternatives for each pavement segment. Then, the metrics for downside risk and upside potential are presented. A comprehensive indicator reflecting decision makers' attitudes towards risk and opportunity is also developed. The network-level M&R optimization problem is then solved while taking into account the various attitudes of decision makers, and their influence on the optimization results is also investigated. At last, a network-level multi-objective optimization (MOO) model is developed considering three objectives: 1) maximizing expected returns (i.e., minimizing the expected total costs in this study), 2) minimizing downside risks, and 3) maximizing upside potential.

2.1 Segment-level M&R optimization

The segment-level M&R optimization problem aims to minimize the sum of discounted agency costs and additional user and environmental damage costs (EDCs) for each multi-lane pavement segment over the planning horizon (20 years in this study). It was addressed through a reinforcement-learning (RL) approach that combines the Twin Delayed Deep Deterministic policy gradient algorithm (TD3) (Fujimoto *et al.*, 2018) and the Wolpertinger Policy (Dulac-Arnold *et al.*, 2015). The main reasons for using the RL approach for segment-level maintenance optimization are (1) RL takes advantage of individual behavioural interactions which enables more efficient search, and (2) RL has been proven by many studies to provide flexibility for decision-making (Yao *et al.*, 2022). Meanwhile, the incorporation of the Wolpertinger Policy allows the RL agent to efficiently learn from large discrete action spaces, thus enabling the model to provide lane-specific M&R strategies. Three RL models were developed for one-way two-, three-, and four-lane pavement segments, respectively.

Figure 1 shows the flowchart of the TD3-Wolpertinger algorithm. The agent is the decision-maker in charge of making M&R plans. The environment includes the things with which the agent interacts, comprising everything outside the agent. In the context of pavement maintenance optimization, it encompasses the road segment itself as well as its surrounding environment and was simulated using a set of probabilistic pavement performance models (Yao *et al.*, 2021) and a reward function. The state refers to the minimum amount of information needed for the agent to make M&R decisions in the environment, which consists of the influential factors in the pavement performance models. The action is the available joint M&R treatment for a multi-lane pavement segment. The reward is the negative of the sum of agency costs and additional user and EDCs between two consecutive time points. Thus, the optimization objective of the model to maximize cumulative rewards is equivalent to minimizing total costs. Agency costs were estimated by summing the material, machine, and labor costs calculated from local reference prices. Additional user costs include additional fuel consumption, tire wear, and vehicle maintenance and repair costs due to the uneven pavement surface relative to the baseline condition (i.e., IRI=1 m/km), as well as work zone vehicle operation and delay costs in comparison to normal operation. The former was calculated using the models developed by Zaabar and Chatti (2014) and the latter was obtained by running the RealCost software (FHWA, 2011). The additional EDCs were estimated by monetarizing the greenhouse gas (GHG) emissions generated from vehicle operation on uneven pavement, as well as raw material consumption and construction equipment operation in M&R activities. The corresponding emission data were collected from different reports, studies, and specifications (Eurobitume, 2011; Stripple, 2001; JTG/T 3832-2018; JTG/T 3833-2018).

To achieve this goal, the agent alternated between interaction with the environment (i.e., M&R action selection, state transition and reward calculation) and policy update. TD3 is built on the actor-critic paradigm, in which the actor determines which action to do, and the critic informs the actor on how good the action is and how it should be improved. At each time step, the agent chose an action based on its current state and policy (i.e., the actor network). Applying the action to the environment gives the next state of the environment and a reward signal. This process is repeated, and all the information obtained is stored in a replay buffer. Then, during the policy update, a small batch of data will be sampled from the buffer to update the network parameters through temporal difference (TD) learning. More details can be found in (Yao *et al.*, 2022).

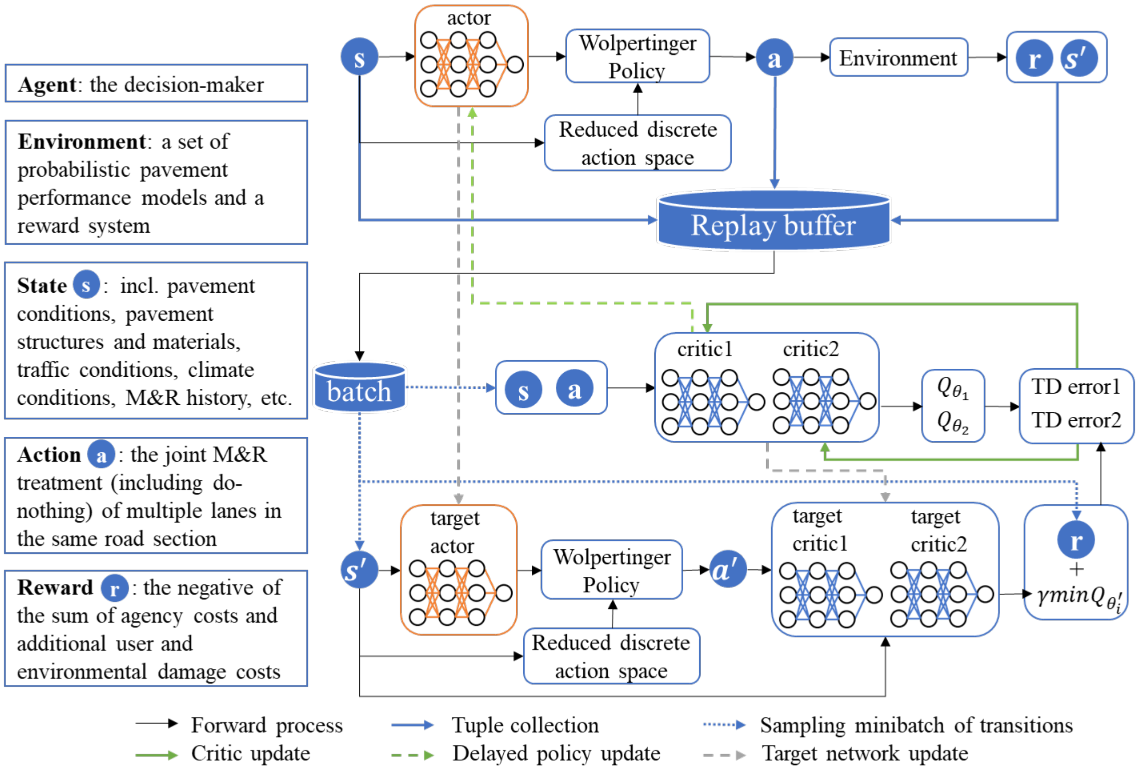


Figure 1. Flowchart of TD3-Wolpertinger algorithm for segment-level M&R optimization (Yao *et al.*, 2022).

After the RL models have converged, two optimal M&R treatment alternatives were identified for each segment based on the ranking of the Q values of all available actions. The reasons for selecting only two optimal alternatives are two-fold. Firstly, the number of available actions for each segment is different and can reach 4193 even after imposing the vertical constraint (Yao *et al.*, 2022). Thus, selecting two optimal alternatives before performing network-level optimization can largely reduce the complexity of the problem, which is also the approach adopted in some previous studies (Guo *et al.*, 2020; Guo *et al.*, 2021). Meanwhile, only the first action in the selected action sequences is incorporated into the network-level model, and network-level optimization is performed on a yearly basis. This also alleviates the limitation caused by selecting only two optimal alternatives to network-level optimization. Secondly, for RL models with large scale state and action spaces, there must exist some rarely visited state-action pairs as they are less promising to be a part of the optimal action sequence. Thus, the expected returns and rankings of action sequences going through these state-action pairs are less reliable, which constitutes one of the reasons why only the two optimal alternatives are selected as candidates for network-level optimization. The Monte Carlo simulation (MCs) was then performed to randomly sample 1000 future deterioration trajectories for each segment starting from the selected current action and following the learned policy thereafter. According to whether "do-nothing" was included in the two optimal actions and whether "do-nothing" was allowed under the current pavement conditions, there would be two or three M&R alternatives for each segment pending for selection in the network-level optimization model. The total cost (i.e., the sum of cumulative agency costs and additional user and EDCs over the planning horizon) and corresponding probability distribution of each M&R alternative can also be determined.

2.2 Metrics for downside risk and upside potential

Apart from the mean-variance model, Markowitz also developed another measure of risk: the semi-variance of returns (Markowitz, 1959), which was considered a more plausible measure of risk. The semi-variance describes the downside variability of returns below a pre-specified benchmark value that is determined based on the decision maker's definition of loss, as shown below:

$$S_{B-}^2 = E\{\min[(X-B),0]^2\} \tag{1}$$

where S_{B-}^2 is the lower semi-variance, S_{B-} is the lower semi-deviation, B is the pre-specified benchmark value, X is the random variable, and E is the expectation operator. While the lower semi-variance measures the uncertainty in losses, the upper semi-variance quantifies the uncertainty in gains:

$$S_{B+}^2 = E\{\max[(X-B),0]^2\} \tag{2}$$

where S_{B+}^2 is the upper semi-variance and S_{B+} is the upper semi-deviation.

In the context of pavement M&R optimization, risk is typically associated with failure to achieve minimum acceptable performance or returns (Ng *et al.*, 2011; Menendez and Gharaibeh, 2017), such as pavement conditions not meeting the prescribed requirements or LCCs exceeding the expected values. Meanwhile, decision makers are generally not averse to variability above benchmark returns and may instead expect to seek upside potential. Therefore, this study employed the lower and upper semi-deviations from a benchmark return to measure the downside risk (i.e., uncertainty in losses) and upside potential (i.e., uncertainty in gains) of an M&R strategy, as illustrated in Figure 2. The return of an M&R strategy is the cumulative rewards or the negative of total costs over the planning horizon. The negative of total costs obtained from the state-of-the-practice hierarchical threshold-based approach (HT) was used as the benchmark. In this way, the risks (opportunities) that the innovative RL models would produce M&R strategies with higher (lower) total costs than the current practice were considered.

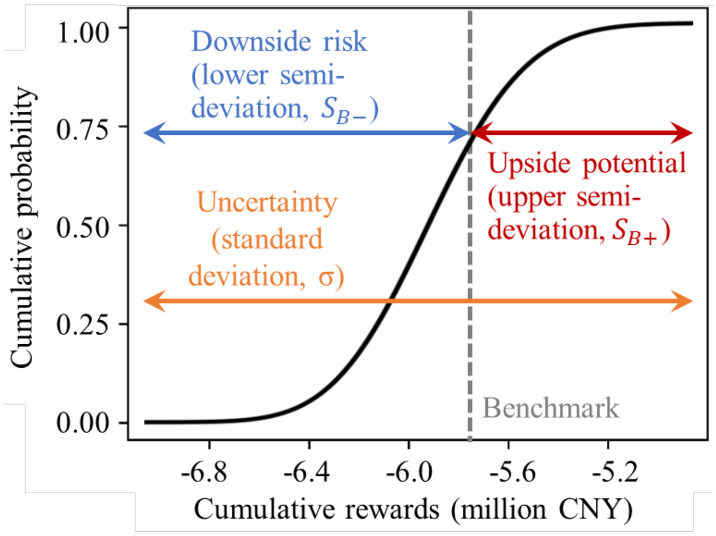


Figure 2. The schematic diagram of downside risk, upside potential and uncertainty.

2.3 A comprehensive indicator reflecting decision makers' attitudes

Distinguishing between lower and upper semi-deviations leads to four different types of attitudes of decision makers, including aversion and neutrality to downside risks, and expectation and neutrality to upside potential (Santos *et al.*, 2017). To measure the extent to which decision makers are averse to risks and expect to opportunities, aversion coefficient to downside risk and expectation coefficient to upside potential were proposed (Santos *et al.*, 2017). A comprehensive indicator measuring the value of a strategy while reflecting decision makers' attitudes towards risk and opportunity was then developed, as given in Eq. (3):

$$\varepsilon(X) = E[X] - c_{dr}S_{B-} + c_{up}S_{B+} \tag{3}$$

where $\varepsilon(X)$ is the value of strategy adjusted to decision maker's attitudes, $E[X]$ is the expected value of returns, c_{dr} is the aversion coefficient to downside risk, and c_{up} is the expectation coefficient to upside potential. Hence, c_{dr} and c_{up} equal to 0 indicate a neutral attitude towards risk and opportunity, respectively. In contrast, higher c_{dr} and c_{up} imply higher aversion to downside risk and higher expectation of upside potential, respectively. Combining the attitudes towards risk and opportunity further derives four comprehensive attitude types, as shown in

Table 2.

Table 2 Decision makers' attitudes towards risk and opportunity.

Attitudes towards risk / Attitudes towards opportunity	Neutrality	Aversion
Neutrality	Neutrality to downside risk and upside potential ($c_{dr} \rightarrow 0, c_{up} \rightarrow 0$)	Aversion to downside risk and neutrality to upside potential ($c_{dr} > 0, c_{up} \rightarrow 0$)
Expectation	Expectation of upside potential and neutrality to downside risk ($c_{dr} \rightarrow 0, c_{up} > 0$)	Aversion to downside risk and expectation of upside potential ($c_{dr} > 0, c_{up} > 0$)

2.4 Network-level M&R optimization

At the network level, the goal is to select the final M&R treatment for each segment while taking into account the attitude of the decision maker, thus allocating a limited budget to the entire pavement network and ultimately minimizing the sum of adjusted total costs for the entire network. The mathematical formulation of the network-level optimization model is shown in Eq. (4a) ~ (4j), with the meaning of each variable given in Table 3.

Minimize:

$$\sum_{n=1}^{N_s}\left[\sum_{i=1}^{2} x_{n,i} TC\_adj(a_{n,i}) + (1-\sum_{i=1}^{2} x_{n,i}) TC\_adj(0)\right] \quad (4a)$$

subject to:

$$TC\_adj(a_{n,i}) = E[TC(a_{n,i})] + c_{dr} S_{B-}(a_{n,i}, B_n) - c_{up} S_{B+}(a_{n,i}, B_n) \quad n = 1,2, \dots N_s, i = 1,2 \quad (4b)$$

$$S_{B-}(a_{n,i}, B_n) = \sqrt{E\left\{\max[(TC(a_{n,i}) - B_n), 0]^2\right\}} \quad n = 1,2, \dots N_s, i = 1,2 \quad (4c)$$

$$S_{B+}(a_{n,i}, B_n) = \sqrt{E\left\{\min[(TC(a_{n,i}) - B_n), 0]^2\right\}} \quad n = 1,2, \dots N_s, i = 1,2 \quad (4d)$$

$$x_{n,1} + x_{n,2} \leq 1 \quad n = 1,2, \dots N_s \quad (4e)$$

$$x_{n,1}, x_{n,2} \in \{0,1\} \quad n = 1,2, \dots N_s \quad (4f)$$

$$a_{n,1}, a_{n,2} \in A_{avail,n} \quad n = 1,2, \dots N_s \quad (4g)$$

$$x_{n,1} + x_{n,2} \geq int(a_{n,1} = 0 \ or \ a_{n,2} = 0) \quad n = 1,2, \dots N_s \quad (4h)$$

$$x_{n,1} + x_{n,2} \geq int(\text{"}do - nothing\text{" } is \ not \ allowed) \quad n = 1,2, \dots N_s \quad (4i)$$

$$\sum_{n=1}^{N_s}\left[\sum_{i=1}^{2} x_{n,i} cost(a_{n,i})\right] \leq Budget \quad (4j)$$

Table 3 Meanings of all variables in the network-level optimization model.

Variables	Meanings
n	Segment ID
N_s	The number of segments in the road network
$a_{n,i}$	The optimal ($i = 1$) and suboptimal ($i = 2$) M&R treatment ID for segment n ($a_{n,i} = 0$ corresponds to do-nothing)
$A_{avail,n}$	The set of available M&R treatment IDs for segment n
$x_{n,i}$	Decision variables: if $a_{n,i}$ is selected, then $x_{n,i} = 1$, otherwise, $x_{n,i} = 0$
$TC\_adj(a_{n,i})$, $E[TC(a_{n,i})]$	The adjusted and expected values of total costs of segment n over the planning horizon when selecting the treatment $a_{n,i}$ for current year and following the segment-level M&R policy thereafter (Yao *et al.*, 2022)
B_n	The benchmark value of the total cost for segment n
$S_{B-}(a_{n,i}, B_n)$, $S_{B+}(a_{n,i}, B_n)$	The lower (i.e., downside risk) and upper (i.e., upside potential) semi-deviations of segment n from the benchmark value B_n when selecting the treatment $a_{n,i}$ for current year and following the segment-level M&R policy thereafter (Yao *et al.*, 2022)
c_{dr}	The aversion coefficient to downside risk
c_{up}	The expectation coefficient to upside potential
$int(\cdot)$	Operator that converts a Boolean value to an integer (i.e., $int(True) = 1$, $int(False) = 0$)
$cost(a_{n,i})$	The cost of treatment $a_{n,i}$
$Budget$	The available maintenance budget for the current year

Note that although the optimization objective of minimizing the sum of adjusted total costs is equivalent to maximizing the sum of returns or cumulative rewards, it makes a difference between Eq. (1) ~ (3) and Eq. (4b) ~ (4d). The M&R treatment denoted by $a_{n,i}$ refers to the joint action of multiple lanes in the same road segment. Thus, the number of available M&R treatments (i.e., the size of $A_{avail,n}$) varies between segments due to the different number of lanes and the constraints that limit the range of M&R options available for a given pavement condition (Yao *et al.*, 2022). Eq. (4e) ensures that at most one treatment would be selected for each segment. As shown in Eq. (4f), $x_{n,1}, x_{n,2}$ are binary variables with values of one for selection, zero for non-selection, and both zero for selecting do-nothing. Therefore, if the optimal and suboptimal treatments already include do-nothing, then $x_{n,1}$ and $x_{n,2}$ cannot both be zero to avoid multiple solutions, as shown in Eq. (4h). Also, Eq. (4i) guarantees that if do-nothing is not allowed for a given pavement condition (Yao *et al.*, 2022), then $x_{n,1}$ and $x_{n,2}$ cannot both be zero either. Eq. (4j) is the budget constraint.

The network-level maintenance optimization problem described above is an integer programming problem that can be solved using the powerful mathematical optimization solver

Gurobi (Gurobi Optimization LLC, 2022). In this study, the gurobipy library, which is a Gurobi Python interface was used to solve the problem. The most common case of ignoring the decision makers' attitudes or assuming a neutral attitude towards risk and opportunity to optimize the network-level M&R strategy for different budget levels was first considered. Next, the effects of decision makers' attitudes on the resulting M&R decisions were investigated by solving the optimization problem with different values of c_{dr} and c_{up}. Finally, the Ɛ-constraint method (Haimes, 1971) was applied to generate the Pareto front for the MOO problem with the objective of minimizing the expected total cost and downside risk while maximizing the upside potential. The Ɛ-constraint method optimizes one selected objective while transforming the other objectives into additional constraints with specified bounds (Haimes, 1971). It was adopted because it is conceptually easy to understand and simple to implement, and its use alone can produce exact Pareto solutions. The Pareto front is composed of a set of solutions (i.e., Pareto optimal solutions) that are non-dominated to each other (i.e., none of the objectives can be improved without sacrificing at least one of the other objectives) but are superior to the rest of solutions in the search space. The derived results were also compared with those of the mean-variance model to demonstrate the superiority of the mean-semivariance method.

3 Case Study

To demonstrate the application and benefits of the proposed network-level optimization model, several case studies based on the highway pavement network in Jiangsu Province, China were conducted. Figure 3 shows the map of the road network involved in the case studies. The orange lines are segments that are included in the network-level optimization, while the light-yellow lines are those that are not included for various reasons (e.g., they are not under the jurisdiction of the central agency, or they do not have complete data). The first case study considered a neutral attitude of decision makers towards risk and opportunity which is the most common case in the practice. The second and third cases solved the network-level M&R optimization problem considering a risk-averse and opportunity-seeking decision maker, respectively. The fourth one assumes that the decision maker is averse to downside risk while expecting upside potential at the same time. Finally, in the fifth case study, we resorted to the MOO technique to generate the Pareto front and compared the mean-semivariance method with the mean-variance model.

Figure 3. The map of the road network involved in the case study.

The various types of data, such as the pavement structures and materials, pavement performance, traffic and climate conditions and maintenance histories, were collected from the PMS in Jiangsu. This information was then integrated and used to separate the expressways into shorter sections. As a result, a segment in this study corresponds to a 1-kilometer one-way highway pavement segment with 2 to 4 lanes (in one direction). A total of 7,109 segments were obtained. Table 4 presents the M&R actions available for a single lane, “do nothing” is also an alternative action. The M&R treatment for a multi-lane pavement segment is therefore a combination of 2 to 4 of these actions. The segment-level maintenance optimization problem was first solved, and two M&R treatment alternatives were identified for each segment (Yao *et al.*, 2022). Based on this, the network-level optimization problem was addressed and the five case studies were performed.

Table 4 The available M&R actions for a single lane (Yao *et al.*, 2022).

ID	M&R treatment	Category
1	Seal coating	Preventive maintenance

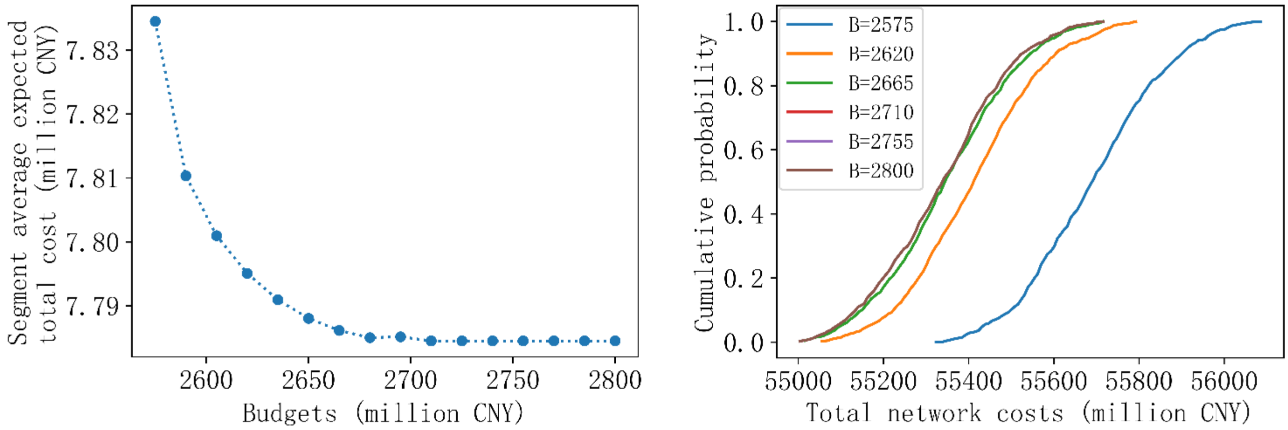
2	Micro-surfacing	
3	Hot-in-place rehabilitation	
4	Fine mill & fill	
5	Thin overlay	
6	Fine mill & fill and thin overlay	
7	Mill & fill the upper asphalt layer	Rehabilitation
8	Overlay with PAC-13	
9	Overlay with ARAC-13	
10	Overlay with SBS modified AC-13	
11	Mill & fill the upper and middle asphalt layer	
12	Mill & fill the entire asphalt layer	

Notes: PAC, ARAC and AC are the porous asphalt concrete, asphalt-rubber concrete, and a dense-graded mixture, respectively, whereas the number “13” denotes the nominal maximum aggregate size in millimeters.

4 Results and Discussion

4.1 Neutrality to downside risk and upside potential

A neutral attitude of decision makers towards risk and opportunity is often the most common assumption in pavement management. It aims to optimize the expected return of M&R strategy under a budget constraint. In this study, this was done by setting c_{dr} and c_{up} both to zero and solving Eq. (4a) ~ (4j). Figure 4 shows the network-level optimization results. Total network cost refers to the sum of agency costs and additional user and EDCs for the entire network over the 20-year planning horizon and averaging its expected value over all segments gives the segment average expected total cost. Figure 4(a) illustrates how the minimum segment average expected total costs change with respect to various budget constraints. This curve can also be considered as a Pareto front derived from the bi-objective optimization problem with the goals of minimizing the segment average expected total cost and minimizing the network-wide summed agency cost for the current year. It reveals that significant reductions in segment average expected total costs can be achieved with small budget increases when the current budget is relatively small. In other words, there are decreasing marginal improvements in segment average expected total cost reductions. Figure 4(b) is the distributions of the total network costs at different budget levels. The same conclusion can be drawn since the cumulative probability curves get closer as the budget increases.



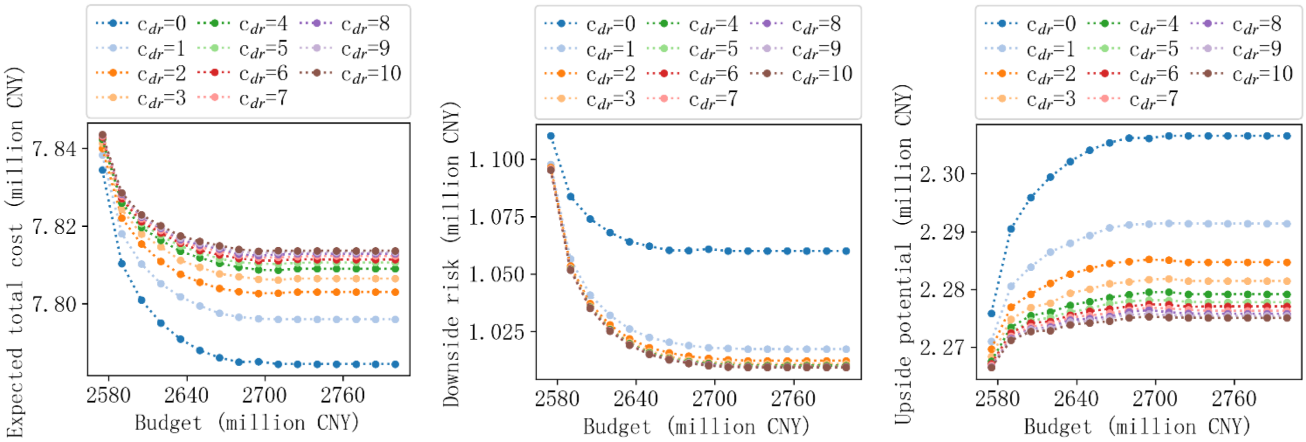
(a) Minimum segment average expected total costs at different budget levels

(b) Distributions of total network costs at different budget levels

Figure 4. Network-level optimization results considering neutral attitudes of decision makers.

4.2 Aversion to downside risk and neutrality to upside potential

In the second case, a risk-averse decision maker who is neutral to upside potential was considered. The extent to which he/she is averse to downside risk is captured by the aversion coefficient c_{dr}, with a larger c_{dr} indicating a greater desire to avoid risk. In this study, c_{dr} varies between 0 and 10, as it was found that further increases in the coefficient do not have a significant effect on the results anymore. Hence, the range of 0 to 10 is considered sufficient to cover the possible variations in expected total costs, downside risk and upside potential. The network-level optimization problem was solved multiple times by varying the c_{dr} from 0 to 10 while keeping c_{up} fixed at 0. Figure 5 shows the optimization results, with Figure 5(a)~(c) illustrating the segment average values of the expected total cost, downside risk and upside potential, respectively. It can be found that at the same budget level, the increase in risk aversion reduced the downside risk, but this leads to a higher expected cost and lower upside potential. In addition, the change in downside risk caused by c_{dr} from 0 to 1 is significantly larger than that produced by c_{dr} from 1 to 10. However, the changes in expected cost and upside potential induced by c_{dr} from 0 to 1 and c_{dr} from 1 to 10 are comparable. This implies that increasing c_{dr} from 0 to 1 effectively reduces downside risk, but a further increase in this coefficient is not advisable because the resulting risk reduction is almost negligible while the expected performance and upside potential of the M&R strategy are greatly affected. Furthermore, increasing budget can simultaneously reduce expected cost and downside risk and increase upside potential at any level of risk aversion, but the marginal effect of doing so is diminishing. Meanwhile, when the currently available budget is tight, seeking more budget can partially or completely offset the negative impact of introducing risk aversion coefficients on expected performance and upside potential.



(a) Segment average expected total cost

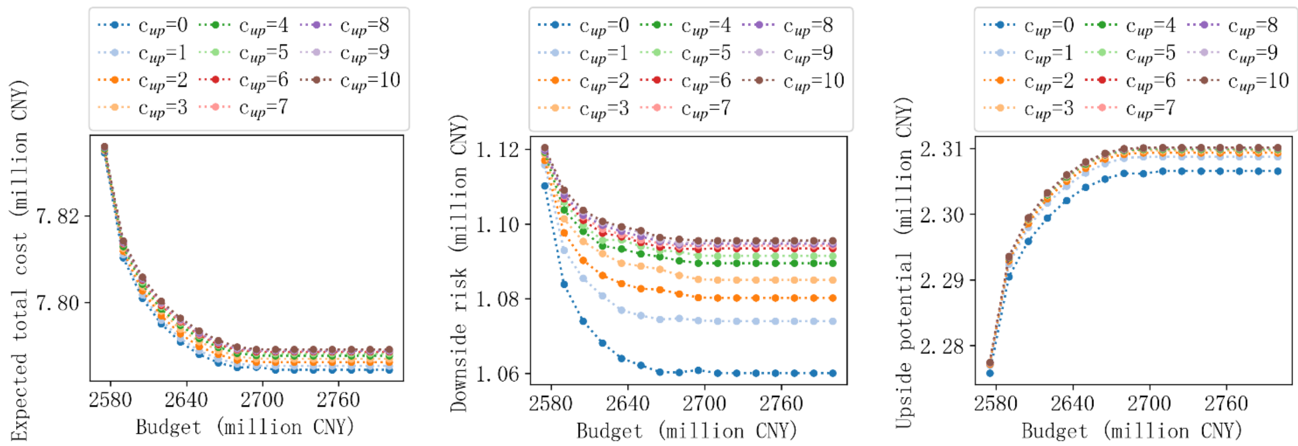
(b) Segment average downside risk

(c) Segment average upside potential

Figure 5. Network-level optimization results considering a risk-averse decision maker.

4.3 *Expectation of upside potential and neutrality to downside risk*

The third case considered an opportunity-seeking decision maker who is neutral to downside risk. Similarly, the extent to which he/she expects to upside potential is measured by the expectation coefficient c_{up}, with a larger c_{up} indicating a greater desire to seek opportunity. In this study, the range of c_{up} was also from 0 to 10 for the same reason as c_{dr}. The value of c_{up} was gradually increased from 0 to 10 while fixing c_{dr} at 0 and re-solved the optimization problem each time c_{up} was changed. Figure 6 shows the corresponding results. It can be found that increasing the expectation coefficient would only marginally increase the upside potential, but at the cost of significantly increasing the downside risk and slightly increasing the expected cost. Meanwhile, when the currently available budget is tight, this negative effect can be mitigated by seeking additional budget. Otherwise, even budget increase will not work due to its diminishing marginal effect. The results indicate that increasing the upside potential requires taking more risks or increasing the maintenance budget.



(a) Segment average expected total cost

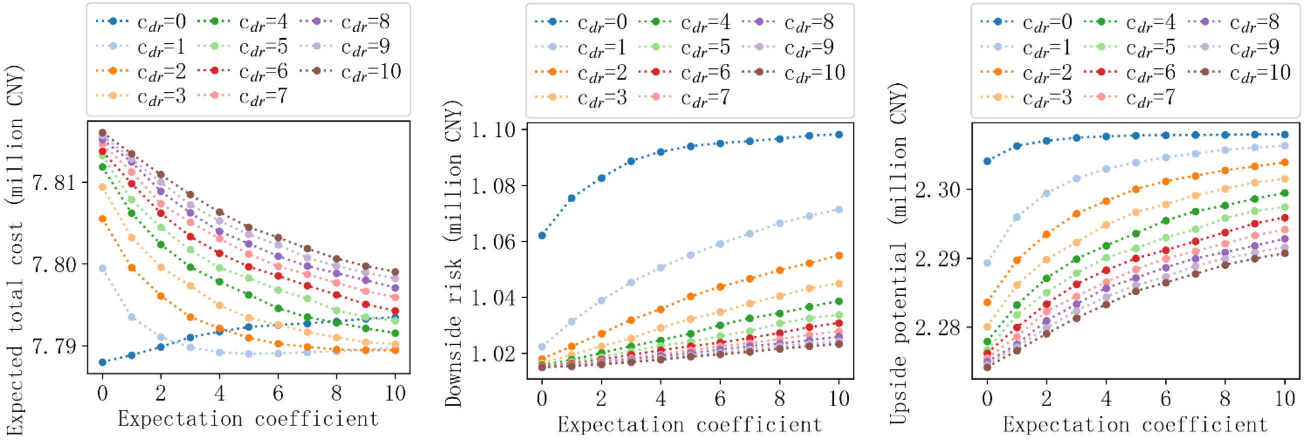
(b) Segment average downside risk

(c) Segment average upside potential

Figure 6. Network-level optimization results considering an opportunity-seeking decision maker.

4.4 Aversion to downside risk and expectation of upside potential

In the fourth case, a risk-averse decision maker who expects opportunity at the same time was considered. The network-level M&R optimization problem was solved for a given moderate budget level (budget=6,850 million CNY) and different combinations of c_{dr} and c_{up}. The results are presented in Figure 7. It can be observed that when decision makers are neutral to downside risk (i.e., $c_{dr} = 0$), a higher expectation coefficient only slightly increases upside potential at the cost of higher expected costs and risks. Conversely, when decision makers are averse to downside risk (i.e., $c_{dr} > 0$), a higher c_{up} not only greatly increases upside potential but also reduces expected costs, although the risk is still increased. Meanwhile, when decision makers are neutral to upside potential (i.e., $c_{up} = 0$), a higher risk aversion reduces downside risk at the cost of higher expected costs and lower upside potential. However, when decision makers expect to upside potential (i.e., $c_{up} > 0$), it is possible to simultaneously reduce downside risk and expected cost by improving c_{dr} from 0 to 1. This means that in some cases, higher upside potential and lower expected costs, or lower downside risk and lower expected costs can be achieved simultaneously by adjusting the values of c_{dr} and c_{up}, but without a larger budget, higher upside potential and lower downside risk can never be achieved at the same time.



(a) Segment average expected total cost (b) Segment average downside risk (c) Segment average upside potential

Figure 7. Network-level optimization results considering a risk-averse and opportunity-seeking decision maker.

Moreover, Figure 7 can guide decision makers in selecting proper aversion and expectation coefficients to reflect their attitudes toward risk and opportunity. As an example, assuming that the decision makers hope to reduce the downside risk without significantly affecting the expected cost and upside potential compared to the case where decision makers' attitudes are ignored (i.e., $c_{dr} = c_{up} = 0$), then, based on the degree of risk reduction desired (e.g., $\Delta S_{B-} \geq 0.02$ million CNY) and the acceptable range of influence on the expected cost (e.g., $\Delta E \leq 0.005$ million CNY) and upside potential (e.g., $\Delta S_{B+} \leq 0.005$ million CNY), the eligible regions in Figure 7 (a) ~ (c) (marked with red boxes in Figure 8) can be found and the appropriate c_{dr} and c_{up} (marked with blue boxes and circles in Figure 8) can be further selected from the intersecting area to perform the network-level optimization. The example selection process is shown in Figure 8.

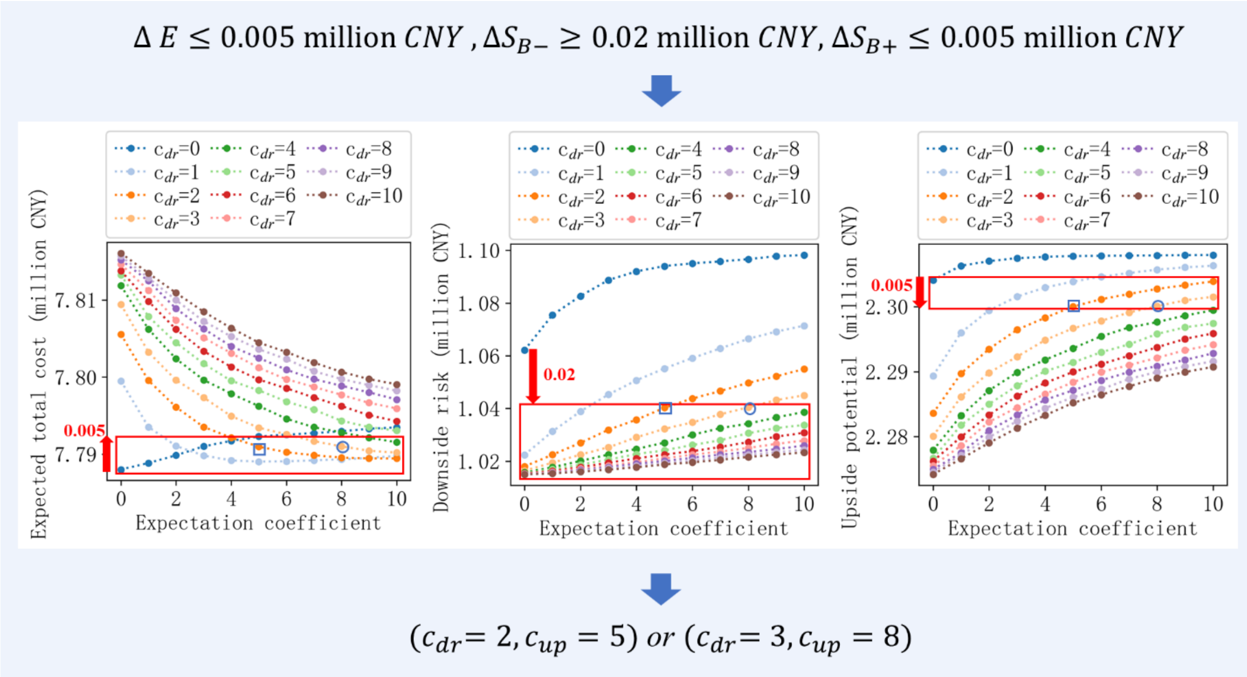


Figure 8. An example of aversion coefficient and expectation coefficient selection.

4.5 Multi-objective optimization

Figure 9 and Figure 10 show the results of network-level MOO, with Figure 9 presenting the Pareto front in the three-objective space and Figure 10 illustrating the trade-offs between two objectives. The results derived from the mean-variance model with various risk aversion coefficients are also plotted as orange dots for comparison. Each blue dot represents a budget allocation scheme corresponding to the decision maker's specific attitude towards risk and opportunity, which provides a unique and optimal trade-off among the expected total cost, downside risk, and upside potential. The general trend is that as the downside risk and upside potential increase, the expected total cost significantly decreases and then slightly increases. The upside potential increases with the increase of the downside risk. This means that, in most cases, reducing risk requires compromising the expected performance and upside potential of the M&R strategy, while the goals of increasing the upside potential and improving the expected performance can basically be achieved simultaneously. Moreover, it can be found that applying the mean-semivariance model allows for a reduction in the expected total cost and an increase in the upside potential while maintaining the same level of downside risk compared to the results of the mean-variance model. In other words, the solutions derived from the mean-variance model are not Pareto optimal.

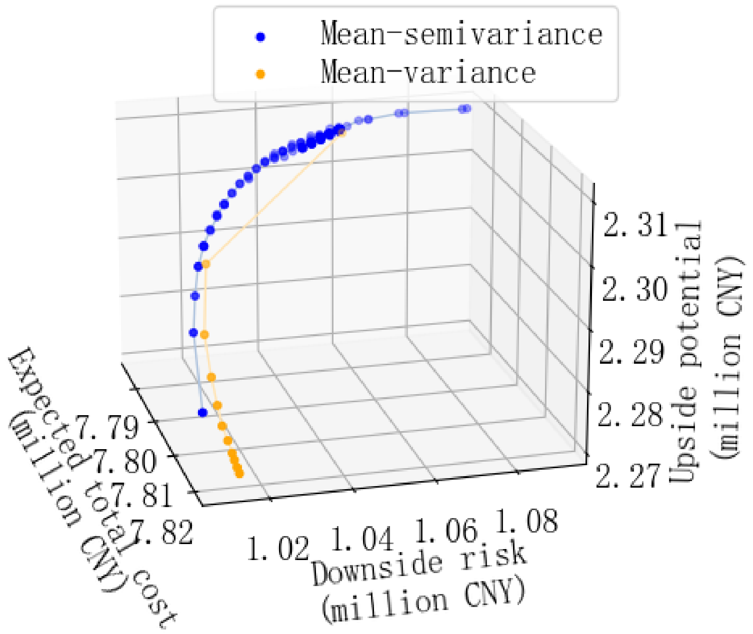
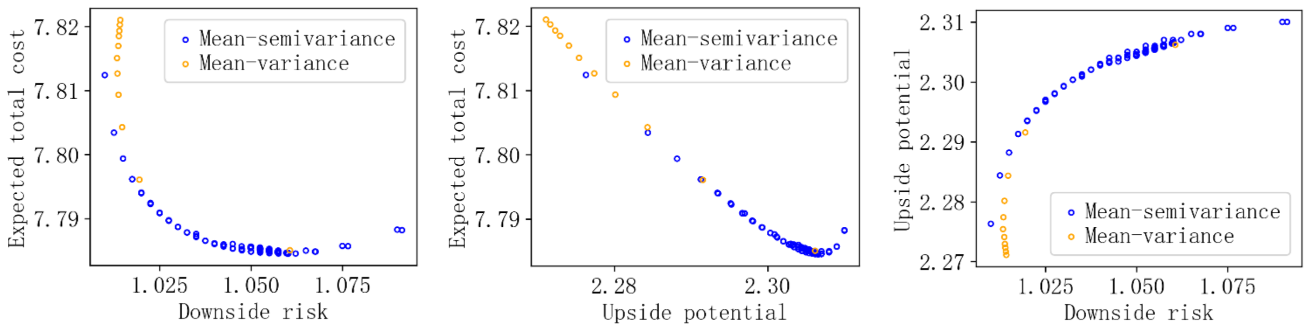


Figure 9. Pareto front of the network-level MOO problem.



(a) Segment average expected total cost and downside risk

(b) Segment average expected total cost and upside potential

(c) Segment average upside potential and downside risk

Figure 10. Trade-offs between two objectives.

5 Conclusions

This study aims to develop a method to quantitatively incorporate decision makers' attitudes into pavement maintenance planning, thus enabling the control of undesirable risks and the pursuit of potential opportunities to varying degrees. To this end, a comprehensive indicator that combines measures of downside risk and upside potential with metrices of decision-makers' attitudes towards them were developed. This indicator constitutes the objective function of the network-level maintenance optimization problem. By varying the values of risk aversion and opportunity expectation coefficients, the impact of decision makers' different levels of risk and opportunity preference on M&R decisions were investigated. An MOO model with the goals of minimizing expected total costs and downside risks and maximizing upside potential was also developed to demonstrate the superiority the mean-semivariance method over the traditional mean-variance method.

A case study based on the highway pavement network in Jiangsu, China, was conducted using the proposed metrics and methods. Regardless of decision makers' attitudes, budget increases can simultaneously reduce expected total costs and downside risks and increase upside potential. Each 1% increase in the current year's budget reduces expected total costs by up to 0.41% and downside risk by up to 5.26% and increases upside potential by up to 0.92%. However, the marginal effect of budget increases is diminishing. That is, when the current budget is relatively small, significant improvements can be achieved with a small budget increase. Otherwise, even an increase in the budget will not have much impact on the performance of the selected M&R strategy.

For risk-averse but opportunity-neutral decision makers, reducing downside risk can be achieved by increasing the risk aversion coefficient, but this inevitably leads to higher expected total costs and less upside potential. Meanwhile, increasing the aversion coefficient from 0 to 1 effectively reduces downside risk, but a further increase result in almost negligible risk reduction while significantly compromising the expected performance and upside potential of the M&R strategy. For opportunity-seeking but risk-neutral decision makers, increasing the expectation coefficient alone could only marginally improve the upside potential, but at the cost of putting additional downside risk, revealing that increasing the upside potential requires taking more risks or seeking additional maintenance budget. For risk-averse and opportunity-seeking decision makers, without a larger budget, they can never realize upside potential improvement and downside risk reduction at the same time. The results can also guide decision makers in selecting proper aversion and expectation coefficients to reflect their attitudes toward risk and opportunity.

The Pareto front of the network-level MOO problem help to visualize the trade-offs among the expected return, risk, and opportunity of the M&R strategy. Reducing risk requires compromising the expected performance and upside potential of the M&R strategy, while the goals of improving the upside potential and expected performance can basically be achieved simultaneously. Applying the mean-semivariance model allows for a reduction in the expected total cost and an increase in the upside potential while maintaining the same level of downside risk compared to the results of the mean-variance model. In other words, the solutions derived from the mean-semivariance model dominate those of the conventional mean-variance model.

The methods and results presented in this study provide insights into how the attitudes of decision makers can be incorporated into pavement maintenance planning and the magnitude of the consequences or costs to increase expected returns and upside potential or reduce downside risk. It helps to control undesirable risks and pursue potential opportunities to varying degrees in the decision-making process. This study also reveals that equating uncertainty with risk yields non-dominated solutions, and therefore distinguishing between uncertainty in gains and losses could produce better results. Despite the contributions of this study, there remain opportunities to further extend this research. For example, a more objective approach can be taken to determine the values of c_{dr} and c_{up}, such as using questionnaires to collect a group of decision makers' preferences for risk and opportunity and establishing a specific relationship between the preferences and the values of c_{dr} and c_{up}. In addition, future research could investigate the risks and opportunities for different stakeholders by using the proposed methodology separately for agency costs, user costs, and environmental impacts.

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Disclosure statement

No potential conflict of interest was reported by the authors.

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