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Impact of Reconstruction Strategies on System Performance Measures: Maximizing Safety and Mobility While Minimizing Life-Cycle Costs

Final Report

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16. Abstract

The objective of this research is to develop a general methodological framework for planning and evaluating the effectiveness of highway reconstruction strategies on the system's performance measures, in particular safety, mobility, and the total cost of network rehabilitation. Transportation networks are characterized by uncertainty that stems from different sources and transportation planners should consider risks involved in uncertainty in model parameters. In this research, Conditional Value at Risk (CVaR) is used to quantify and measure the risk in pavement performance and travel demand. First, a method of constructing risk-based rehabilitation policies for a network of pavement facilities that ensures a specific quality level is introduced. Second, to enhance network mobility, several optimization models to minimize travel time for all paths connecting the same origin and destination pair is presented. Finally, to improve network safety during capacity expansion decisions, two models are presented to reduce accident rate by changing the ratio of flow to the link capacity to reduce injury and fatal accidents and property damage accidents.

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DISCLAIMER

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EXECUTIVE SUMMARY

Transportation agencies have traditionally considered the pavement condition index across the network, network travel time and safety as three measures for determining the need for improvement actions. With limited funding availability, achieving a desired level of service across all measures of network quality indicators requires an effective resource allocation decision making scheme whenever network intervention action is needed. This research aims at building models that can be utilized for resource allocation decision making under different service levels scenarios. Assuming a certain level for each measure of service quality, the model is expected to devise actions that will satisfy the desired quality level under certain risk level. In this research, Conditional Value at Risk (CVaR) is used to quantify and measure the risk in pavement performance and travel demand. Such an approach requires defining and applying an effective level of service for each network quality measure based on risks involved. In this study, β-CVaR is used to quantify and measure risk.

In the second chapter, a method of constructing risk-based rehabilitation policies for a network of pavement facilities that ensures a specific quality level is introduced. The model is formulated in the Markov Decision Process framework with risk-averse actions and transitional probabilities that are subjected to the uncertainty in the pavement performance. When it comes to making short-term rehabilitation decisions when budget is limited, transportation agencies can either chose to distribute their resources on the sole basis of cost/benefit ratios, or base the recourse allocation decisions on narrowing the gap among the quality level of facilities. Comparing the results from two models that each representing these approaches clearly indicates the advantage of fair allocation.

In the third chapter, network mobility enhancement during capacity expansion decisions is discussed. Given a network of m links, several models to minimize the total travel time over all paths that connect origin destination pairs are presented. All models take the risk in travel demand realization into consideration. The computational results from the three models shows that system optimal network design problem with minimum path travel time can provides the best travel time over all paths connecting the same O-D pair. Transportation planners can use the results from this model and determine the recourses required to further improve path travel times.

In the forth chapter, network safety enhancement provisions are incorporated into capacity expansion decisions. The two safety measure indicators considered in this study are fatal and injury accident rate and property damage accident rate.

CHAPTER 1: INTRODUCTION

The network of transportation infrastructure plays an essential role in the nation's overall economy. Seventy-four percent of the $8.4 trillion worth of commodities in the U.S. is transported by trucks on the state's highways. The current transportation infrastructure is the result of several decades of planned development, and now transportation agencies need to dedicate an ample amount of resources to maintain it in acceptable condition. In 2000, the total expenditure by all levels of government on transportation infrastructure was $64.6 billion. However, the Federal Highway Administration (FHWA) estimates that the spending by all levels of government would have to increase by 17.5% to reach its projected $75.9 billion cost-to-maintain level, and 65.3% to reach its $106.9 billion cost-to-improve level. (*1*) The existing funding limitations highlight the importance of effective resource allocation decisions. The goal of this research is to develop optimization models that will help network planners in making cost effective resource allocation decisions whenever network intervention actions are necessary.

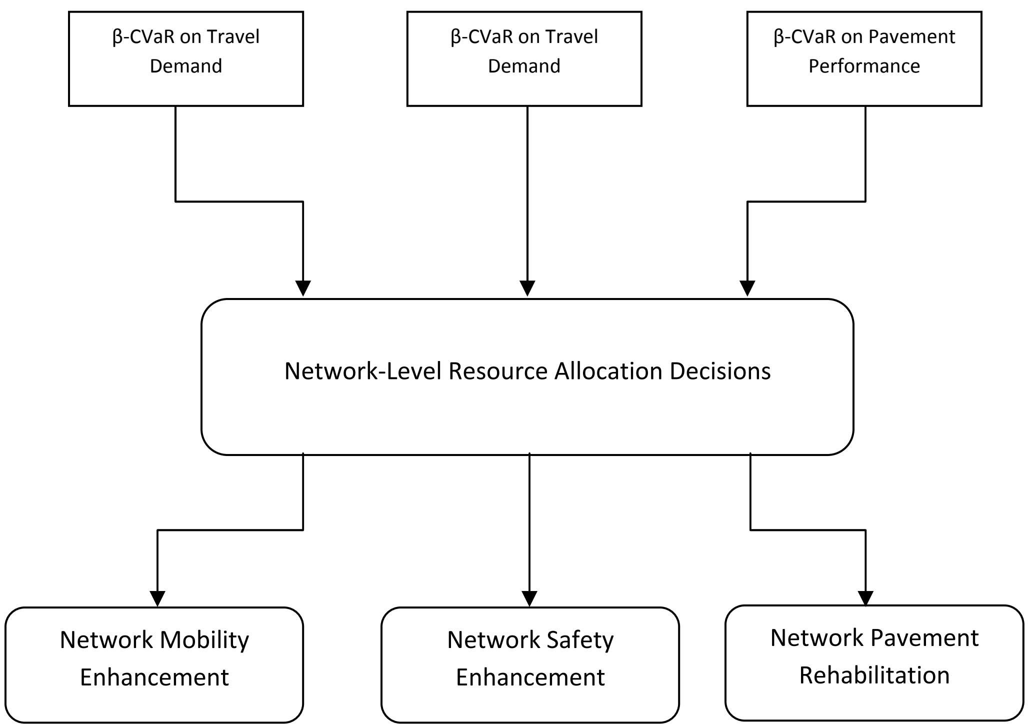

FIGURE 1 Optimal Network-Level Rehabilitation and Expansion Decisions

Figure (1) shows the methodological framework under which this study has taken place. The network-level decision making framework is expected to improve quality of service in terms of pavement condition, mobility and safety.

This report is organized as follows: in chapter 2, a method of constructing risk-based rehabilitation policies for pavement facilities that ensure a specific quality level is presented. The model is formulated in the Markov Decision Process framework with risk-averse actions and transitional probabilities that are subject to the uncertainty in the pavement performance model. The well known Conditional Value at Risk (CVaR) is used as the measure of risk. The steady-state risk-averse rehabilitation policies are modeled assuming no budget restriction. To address the short-term resource allocation problem when the required resources to apply long-term actions exceeds the available short term resources, two LP models are presented to generate short-term network-level polices with different objectives.

In chapter3, several optimization models to allocate resources for maximum mobility under uncertainty in network travel demand are presented. Any change in network condition (either change in capacity or considerable change in pavement condition) will change the driver's route choice or user equilibrium; therefore, network mobility can be enhanced during capacity expansion decisions.

In chapter 4, based on the relationship between network flow accident rates, two optimization models to improve safety during network expansion decision making is presented. Finally, the summary and conclusion of the results is provided in chapter 5.

CHAPTER 2: RISK-BASED NETWORK-LEVEL REHABILITATION DECISIONS

INTRODUCTION

Maintenance and rehabilitation (M&R) activities are generally capital intensive projects in particular for severely utilized facilities. While determining and deploying optimal M&R policies has always been an important part of pavement management systems, the existence of pavement facilities with poor condition along with the budget limitation makes the resource allocation decisions even more important. Over the years a number of models were developed to obtain long-term steady-state policies based on the Markov Decision Process (MDP). However, these models do not take into account risk associated with the effectiveness of rehabilitation actions. They rely on estimated transitional probabilities and short-term policies that seek to take the current condition to the steady state condition, hence their effectiveness is strongly dependent on the accuracy of the deterioration process predictions.

The objective of this chapter is to develop a modeling process for determining long- and short-term rehabilitation policies that take into account the risk associated with pavement performance and use the Conditional Value at Risk (CVaR) as a risk measure for both long- and short- term resource allocation decisions. Such process links the steady-state policies from MDP and the short-term network level allocation.

BACKGROUND

Markov Decision Process (MDP) has been the primary modeling framework for determining the network M&R policies. State-of-the-art infrastructure management systems include MDP to model the network and use dynamic programming techniques to solve for optimal policies. The first application of MDP for pavement maintenance was introduced by Arizona Department of Transportation, in 1979. ADOT developed a pavement management system to improve the allocation of its limited resources while ensuring a certain level of pavement performance quality. The data for the model is gathered based on the inspection of the current condition of the facilities as well as the expectation of the future condition given an action among a finite set of actions performed on the facility. The description of the model is presented in (*2*).

M&R policy optimization models based on the MDP framework can be found in Carnahan et al. (*3*), Feighan et al. (*4*), Gopal and Majidzadeh (*5*). In such formulations, facility states are considered in discrete states and the deterioration process is represented by discrete time transitional probabilities. The Markovian assumption of these models implies that the condition of the facility at time t+1 only depends on the condition in the start of time t and the action applied to the facility. Madanat and Ben-Akiva (*6*), Madanat (*7*) introduced the latent Markov decision processes to account for uncertainly in the current measurement of the facility. Mbwana and Turnquist (*8*) presented a network level optimization model based on MDP for pavement management systems with suggestions for the short-term allocation of resources. Guigner and Madanat (*9*) presented a model for joint optimization of the M&R and improvement policies in a network of infrastructure facility. Smilowitz and Madanat (*10*) extended the LMDP model to policies that include network level constraints. Durango et al. (*11*) combined this model with the inspection decisions and presented an adaptive optimization model to find the optimal policies under performance model uncertainty.

In these models, deterioration is represented as transitional probabilities that are either estimated from expert opinion or empirical data for every single facility. A common approach to solve these models is by making the infinite time horizon assumption and transforming the MDP into a linear programming model for which efficient algorithms exist. A problem arises when this approach is implemented on the network level with the short-term budget restriction. Backward recursion is the common approach to solve MDP in the finite horizon. Adding budget restriction will result in the exponential increase of state variables and makes it computationally expensive to solve the model to optimality.

Another framework to model M&R activities is the optimal control framework with continuous maintenance actions and states. The objective of these models is to minimize the total life cycle costs over a specific time horizon. Tsunokawa and Scofer (*12*) introduced an optimal control approach to approximate the optimal timing and intensity of maintenance actions. Li and Madanat (*13*) presented optimal policies under steady state condition and Ouyang and Madanat (*14*) assuming deterministic deterioration modeland provided the exact and approximate optimal solutions under finite horizon condition while rehabilitation policies are obtained. The models in this framework are specific to single facility with no budget restriction assumption.

Deterioration Uncertainty

In MDP based models, the deterioration process is represented by the transitional probabilities. Two common approaches to estimate transitional probabilities are by expert opinion or from empirical data. Both approaches are prone to ample errors and subjectivity and can result in solutions that may not be reliable.

Deterioration of pavement structure is a complex process. For example, environmental factors and traffic load are two factors in the pavement roughness deterioration and are associated with high level of uncertainty. Several works in the literature specifically address the uncertainty in the pavement performance model. Li et al. (*15*) discussed the importance of accurate prediction of pavement deterioration in the determination of pavement M&R intensity and frequency policies and presented the Nonhomogeneous MDP to determine pavement deterioration rates in different stages. Majidzadeh and Harper (*16*) used Bayesian updating to update the parameters of the deterioration model. Kuhn and Madanat (*17*) proposed robust optimization models to obtain policies that are valid for a collection of transitional probabilities. Durango and Madanat (*18*) introduced an optimal control model where the uncertainty in the deterioration model is represented by a probability mass function of deterioration rates and instead of updating the parameters of the deterioration model, the probability mass function of deterioration rates is updated. Madanat et al. (*19*) proposed an open loop feedback control model in which model parameters are updated sequentially after every inspection round. Durango and Madanat (*20*) assumed deterioration as an unknown mixture of known performance models taken from a finite set of performance models and presented an optimization model to find joint inspection and maintenance polices.

In this study, the deterioration process parameters are assumed to be random variables with known distributions. To manage the uncertainty in the model, a qualitative measure of risk is developed to obtain rehabilitation actions that satisfy a certain performance level within a specific planning horizon. This quantitative measure is essential in both finding the optimal steady state polices that minimize the long-term cost of the network rehabilitation actions and in the short-term budget allocation problem. The purpose of the next section is to define and construct such measure of risk.

CONDITIONAL VALUE AT RISK

Value at Risk is a widely used measure of risk that specifies the maximum risk in a certain confidence level. Conditional Value at Risk (CVaR), also known as Mean Shortfall or Tail VaR is an alternative measure of risk with more attractive properties such as sub-additivity and convexity, which makes it a good measure of risk for optimization modeling. By definition, β-CVaR is the expected loss in the β percent of the worst case scenarios. The relationship between VaR and CVaR and how they can be calculated in our model follows.

Consider a network of M facilities with $i = 1, .., M$ the index set of facilities and define x_i be the amount of budget allocated to facility i. Denote by $f_i(x_i, s_i)$ the loss function associated with decision variable x_i and the random variable $s_i \in S_i$, where s_i is the set of all possible condition states of the facility i. The probability distribution of s_i is assumed to have density of $p(s_i)$. The probability that $f_i(x_i, s_i)$ does not exceed threshold α is given by (*21*):

$$\Psi(x_i, \alpha) = \int_{f(x_i, s_i) \leq \alpha} p(s_i) ds_i \qquad (1)$$

As a function of α for fixed x_i, Ψ is the cumulative distribution function for the loss associated with x_i. The β-VaR and β-CVaR for facility i and the loss random variable associated with x_i and any probability level β in $(0,1)$ is denoted by $\alpha_\beta(x_i)$ and $\phi_\beta(x_i)$:

$$\alpha_\beta(x_i) = min\, \{\alpha \in R: \Psi(x_i, \alpha) \geq \beta\} \qquad (2)$$

$$\phi_\beta(x_i) = (1 - \beta)^{-1} \int_{f(x_i, s_i) \geq \alpha_\beta(x_i)} f(x_i, s_i) p(s_i) ds_i \qquad (3)$$

In this study, pavement roughness is considered as the only measure of pavement quality. As Equation 3 indicates, to calculate β-CVaR for each facility, the probability distribution of pavement roughness at the end of the planning horizon must be present. Figure (2) depicts how risk-based rehabilitation decisions are made using CVaR as the measure of risk. First, for each facility the distribution of future states at the end of planning horizon for each rehabilitation action is simulated.

From these distributions, the actions that satisfy the CVaR level with their corresponding transitional probabilities are derived. Based on these data, the long-term model produces the steady-state risk-averse solution assuming no budget constraint for each facility. At any given year, the transportation agency reviews the facilities that are due for rehabilitation action and checks to see if sufficient resources are available to implement the optimal solutions. If there is a budget shortage, a resource allocation decision is made by solving one of the short-term models. Each part of the models will be discussed with more details in the next sections.

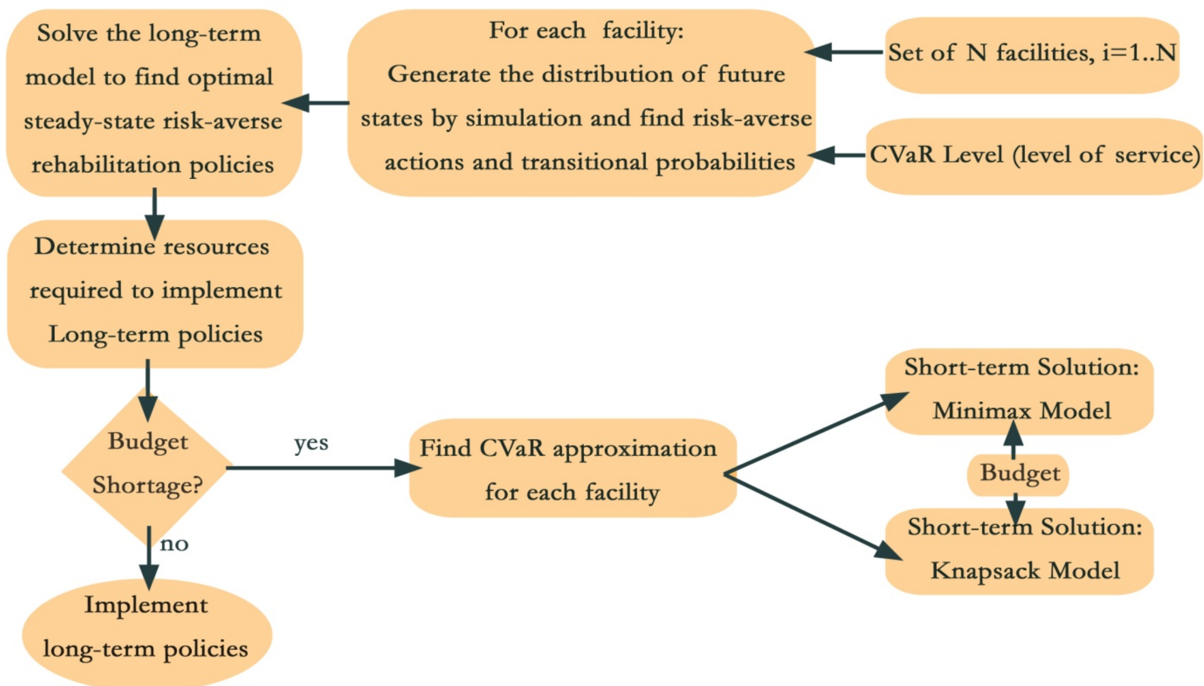

FIGURE 2 Conceptual Decision-Making Model

LONG-TERM RISK-AVERSE DECISIONS

Determining the optimal long-term rehabilitation policies is the initial step in modeling process. It is assumed that the long-term rehabilitation policies are designed to keep the network in a stable condition in the steady-state. MDP is the primary framework for modeling M&R policies in which pavement performance is represented by transitional probabilities under different actions. The objective of most of the models in the literature is to minimize the total cost that consists of both agency and user cost. To deal with uncertainty in the deterioration process, this objective can be replaced by finding rehabilitation policies that maintain the system in an acceptable quality level over any given period of time with minimum cost. In this model, instead of seeking the tradeoff between users' costs and the agency cost, optimal rehabilitation decisions can be generated based on the guaranteed pavement quality level to avoid the subjectivity that users' costs model brings.

To construct such a model, two main inputs in MDP must be altered. First, the action set must only consist of actions that always satisfy a certain level of risk. Second, the transitional probabilities corresponding to the actions in the action set should be estimated from the probability distribution of the future states at the end of the planning horizon. The pseudo-code for generating the risk-averse actions and transitional probabilities by simulation is shown in Figure (3).

```
- Given: The deterioration function y = f(s0, τ, X); X ~ N(μ, σ)
- Initialize: β-CVaR, Planning Horizon τ, Initial State s0, A= {1..N} set of
actions, S= {1..M} set of states, A′, Π′ updated actions and transitional
probability sets.

Begin
  A′ ← ∅
  Π′ ← ∅
  z_a ← ∞
 For each a ∈ A
   For(i=1:MAX)
     Generate random number x_i
      y_i ← f(s0, τ, x_i)
    end;
  ϕ_a ← Generate distribution of future states for action a
  z_a ← β-CVaR {ϕ}
  If (z_a ≤ β − CVaR) {
     A′ ← A′ ∪ a
     π_{a_{β−CVaR}} ← Transitional probabilities corresponding to a
                          Π′ ← Π′ ∪ π_{a_{β−CVaR}}
  }
End
```

FIGURE 3 Pseudo-Code for Determining Risk-Averse Transitional Probabilities

Risk-Averse Actions

To guarantee that the network will always satisfy the quality requirement, all actions in the action set must be risk-averse. The action set includes actions that start from the minimum overlay that will satisfy the risk requirement, to the maximum feasible rehabilitation intensity. Using simulation, the distribution of facility condition with an initial quality level under application of rehabilitation actions is simulated.

From the simulation results, for each initial state the corresponding actions that satisfy the specified risk are determined and the corresponding transitional probabilities are computed. The optimal risk-averse polices can be obtained by solving the MDP with the new transitional probabilities each representing a risk-averse action.

In the case when the distribution of facility condition under different rehabilitation actions continues, the state-space should be discretized by a finite grid approximation to solve the model under the MDP framework. In the next section, the linear programming formulation of MDP for the long-term steady-state risk-averse policies is presented.

Model Formulation

A Markov Decision Process is a tuple, $(S, A, P_{.}(\cdot,\cdot), C(\cdot,\cdot))$ in which the state of the system in period t is $\{S_t, t = 0,1,2,..\}$ and $S = \{1,..,M\}$ is the finite state-space, $A = \{1,..,N\}$ is the finite action space. Applying action $A_t = a$ in state $S_t = i$ results in a cost $C(i,a)$. $P_a(i,j)$ is the probability that action a in state i at time t will lead to state j at time $t + 1$. It is assumed that the system has the following Markov property:

$$P_a(i,j) = P(S_{t+1} = j \mid S_t = i, A_t = a) = P(S_{t+1} = j \mid S_t = i, A_t = a, S_{t-1}, A_{t-1}, .., A_0, S_0)$$

In a stationary infinite horizon Markov decision process, the steady state probabilities are independent of the initial state of the system. Let λ be the discount factor and the policy f be a mapping from action space to state space i.e an action a is chosen if the system is in state i. In the long run, the average cost per stage should be constant regardless of the initial state. The total expected discounted cost under policy f is given by the following value function (*22*):

$$v_\lambda^f(i) = \mathrm{E}_f\left[\sum_{n=1}^{\infty} \lambda^n C[(S_n, A_n) | S_0 = i]\right], \qquad i \in S \qquad (4)$$

The optimal value function, is given by

$$v_\lambda^*(i) = \inf_{f\in F} v_\lambda^f(i) \tag{5}$$

where F is the set of all possible policies.

Let $\alpha(j)$, $j \in S$ be positive scalars such that $\sum_{j\in S} \alpha(j) = 1$, and $P_a(i,j)$ represent the transitional probabilities corresponding to action a, the following LP can be used to solve (5):

$$\max \sum_{j\in S} \alpha(j)\, v(j) \tag{6}$$

subject to

$$v(j) - \sum_{i\in S} \lambda\, P_a(i,j) v(j) \le c(i,a) \quad j \in S, a \in A(a) \tag{6a}$$

$$v(j) \ge 0, \qquad j \in S \tag{6b}$$

Let $x(i,a)$ be the average number of periods during which facility is in state i and action a is taken, the dual linear program can be formulated as follow:

$$\text{Min} \sum_{i\in S} \sum_{a\in A(i)} c(i,a)x(i,a) \tag{7}$$

subject to

$$\sum_{a\in A(i)} x(i,a) - \sum_{i\in S} \sum_{a\in A(i)} \lambda\, P_a(i,j)x(i,a) \ge \alpha_j, \qquad j \in S, \tag{7a}$$

$$(1-\beta)^{-1} \sum_{f(x_i,s_i) \geq \alpha_\beta(x_i)} f(x_i, s_i) P_a(s_i, j) ds_i \leq R \qquad j \in \text{S}, \text{a} \in \text{A} \tag{7b}$$

The solution of (7) - (7b) is a one-to-one mapping from action-space to state-space. This solution represents the long-term M&R policies, designed to keep the network in a stable condition in the infinite time horizon. The budget restrictions are relaxed for the long-term model but they can be added as a constraint to the model.

Short-Term Budget Allocation Decisions

While in the steady state facilities will be in a good condition, in the short-term, there will be facilities with a poor condition that require intensive rehabilitation. The required resource to apply these actions in most cases exceeds the available annual or short-term budget. In such cases, transportation agency has to make the short-term resource allocation decisions. Either resources should be assigned fully to some facilities while rehabilitation action is deprived to the others, or resources should be distributed among facilities to attain a lower CVaR variation across facilities in the network. The short-term model is based on the linear approximation of the CVaR in the short-term. The method of finding these approximate functions is discussed in the next section.

CVaR Approximation

To determine the amount of resources required to achieve a certain level of CVaR for each facility, the approximation of CVaR subject to different actions is required. This approximation can be derived from the distribution of roughness under different actions in the short-term. First, the CVaR level that can be achieved under each action is calculated from the corresponding distribution. The CVaR approximation function can be obtained from linear or polynomial fitting of these discrete points. Figure (4) shows the linear approximation of CVaR under different rehabilitation actions. In the next section, the short-term model formulations are presented.

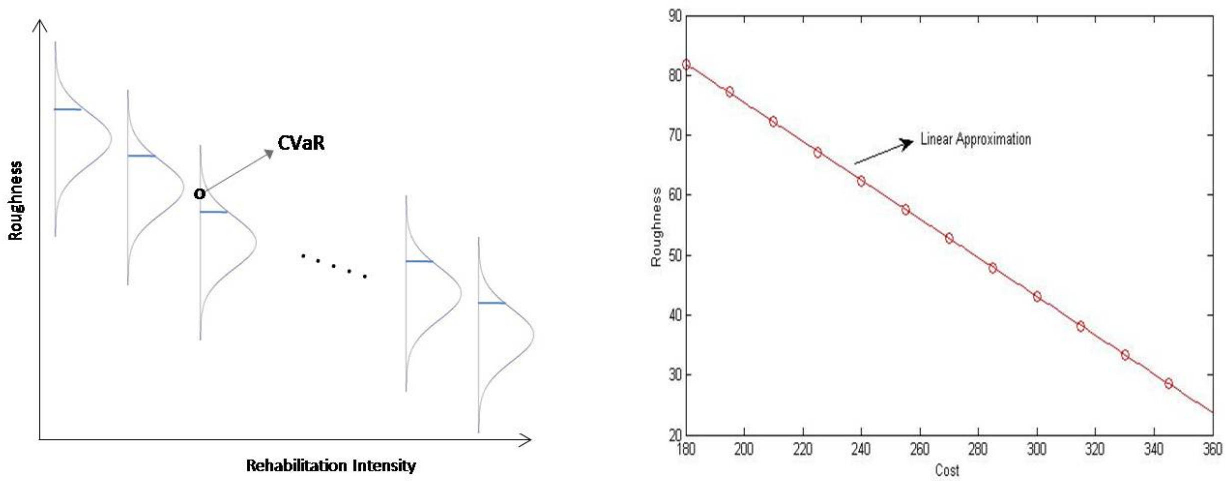

FIGURE 4 CVaR Approximation

Model Formulation

Denote by $\mathcal{L}(x_i)$ the linear approximation of the short-term CVaR, by x_i the budget allocated to facility i, by B_T the annual budget available to agency and by β-CVaR the upper bound on the network CVaR and by $\beta - CVaR(i)$ the CVaR corresponding to facility i. (8) - (8d) is the Minimax model formulation to minimize the highest CVaR of all facilities.

$$\min \beta - CVaR \quad (8)$$

Subject to

$$\beta - CVaR(i) \leq \beta - \mathrm{CVaR}, \quad i \in I \quad (8a)$$

$$\mathcal{L}(x_i) = \beta - \mathrm{CVaR(i)}, \quad i \in I \quad (8b)$$

$$\sum_{i \in I} x_i \leq B_T \quad (8c)$$

$$LB_i \leq x_i \leq UB_i, \quad i \in I \quad (8d)$$

Constraint (8a) bounds all facilities by the highest CVaR, constraint (8b) gives the CVaR with the allocated budget, and constraint (8c) limits the sum of allocations by the total budget and constraint (8d) bounds allocation by the lower and upper bounds.

The model in (9) - (9c) is the Knapsack model formulation with the objective of minimizing the total CVaR over all facilities. Constraint (9a) gives the CVaR for the allocated budget, constraint (9b) limits the sum of allocations, and constraint (9c) bounds allocation by the lower and upper bounds.

$$\min \sum_{i \in I} \beta - CVaR(i) \tag{9}$$

subject to

$$\mathcal{L}(x_i) \leq \beta - \mathrm{CVaR(i)}, \qquad \mathrm{i} \in \mathrm{I} \tag{9a}$$

$$\sum_{\mathrm{i} \in \mathrm{I}} x_i \leq \mathrm{B_T} \tag{9b}$$

$$\mathrm{LB_i} \leq x_i \leq \mathrm{UB_i}, \qquad \mathrm{i} \in \mathrm{I} \tag{9c}$$

The Minimax model yields a solution with lower variation in the quality level of facilities across the network in the cost of slightly lower total quality level for all facilities. The Knapsack model will generate a solution with high variation among the quality level of facilities but with the total CVaR that is lower than the Minimax model. The detail of the numerical results is discussed in the next section.

Numerical Results: Network Rehabilitation Decisions

The continuous pavement state model proposed in (*17*) for overlay and roughness improvement is used for computational results. Let $G(w_i, s_0)$ denote the roughness after applying w_i mm of overlay on the pavement i with s_0 as the initial roughness, then:

$$G(w_i, s_0) = \frac{g_1 w_i}{g_2 + g_3/s_0} \tag{10}$$

where: $w_i \leq g_2 s_0 + g_3,$

$$g_1 = 0.66, \quad g_2 = 0.55, \quad g_3 = 18.3 \tag{11}$$

The agency cost function:

$$M(w) = m_1 w + m_2$$
$$m_1 = 3000 \text{ \$ /km}, \quad m_2 = 150{,}000 \text{ \$ /km} \tag{12}$$

The deterioration model is generally considered as an exponential function of time as follows:

In this analysis, a network of 20 facilities with different initial conditions is considered. The network is depicted in Figure (5). The number on each edge represents the initial roughness of the facility. The deterioration parameter f is assumed to be a random variable normally distributed with μ=.05 and $\sigma^2 = .01$ for all facilities. First, the long-term risk-averse rehabilitation policies that satisfy the 90%-CVaR level of 45 QI (QI = 13 IRI) is determined as follows.

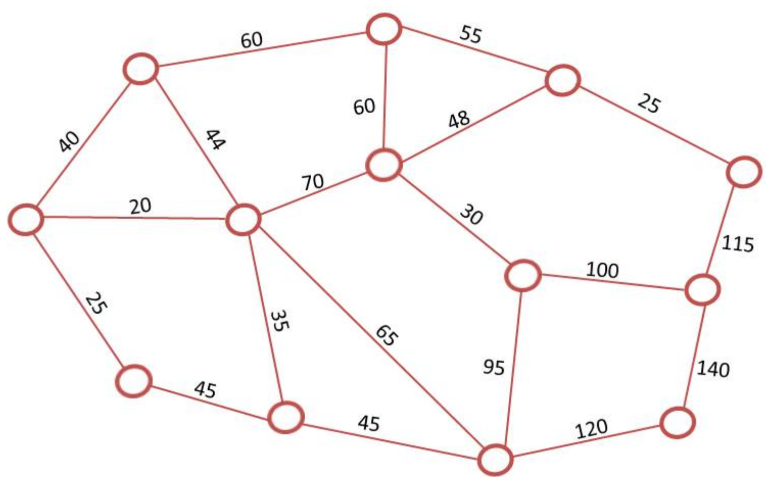

FIGURE 5 Network of Pavements

The continuous state-space of [20,50] interval is discretized into a grid of 16 discrete points. For each roughness level, the distribution of roughness in the 10-year planning horizon is constructed using

Monte-Carlo simulation. Figure (6) shows the distribution of facility's condition under different rehabilitation actions.

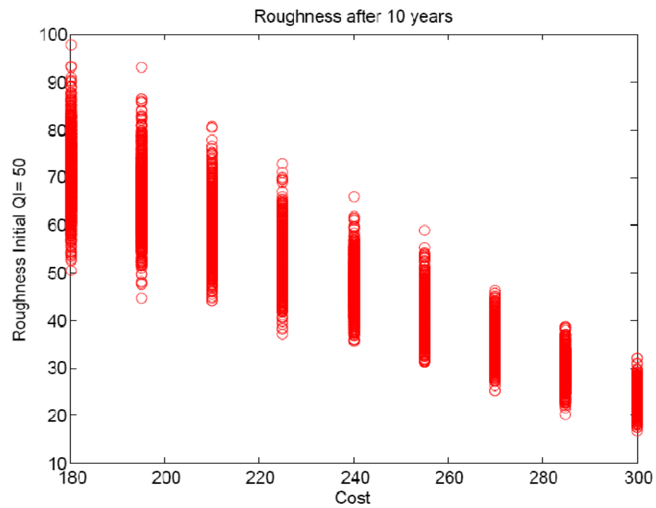

FIGURE 6 Roughness Distributions

Long-term Solution

To demonstrate the approach, the feasible actions are assumed to be the minimum, medium and high intensity rehabilitation. The minimum rehabilitation action is the one that satisfies CVaR with minimum cost. The transitional probabilities for each of these actions along with the cost of actions at each state are generated. Table (1) and (2) show the cost of action in each state and optimal long-term risk-averse rehabilitation actions, respectively, that are obtained by solving long-term model. As shown in Figure (6), the increase in rehabilitation intensity will result in lower roughness variation in the long run. The optimal solution shows many more maximum rehabilitation actions with minimum rehabilitation. This is not surprising since intense rehabilitation will be more effective in reducing the variance of the roughness.

TABLE 1 Cost of Rehabilitation Actions

Action	State															
	20	22	24	26	28	30	32	34	36	38	40	42	44	46	48	50
Min	180	180	180	180	180	195	210	210	225	225	240	240	255	255	270	270
Mid	210	210	210	210	210	225	225	240	240	240	255	255	270	270	270	270
Max	240	240	255	255	255	255	255	270	270	270	270	285	285	285	285	285

TABLE 2 Optimal Rehabilitation Actions

State	20	22	24	26	28	30	32	34	36	38	40	42	44	46	48	50
Action	Min	Min	Mid	Mid	Min	Mid	Max	Mid	Max	Max	Max	Max	Max	Max	Max	Max

Short-term Solution

Table (3) summarizes the comparison of the solution that each short-term model generated on the network of 20 facilities with various initial conditions. As it can be seen in the table, the budget is limited to 4.5$ million that is below the required budget to maintain the network at 45 QI. In the Knapsack solution, there are few facilities with very poor quality while in the Minimax solution all facilities' quality is bounded by 60.95 but with a slightly higher total CVaR. Comparing the standard deviations of the two solutions suggests a much better distribution of facility quality in the Minimax solution.

TABLE 3 Results of the Short-Term Models

Facility	Initial Condition Index (QI)	Minimax Model		Knapsack Model	
		Budget	CVaR	Budget	CVaR
1	40	180	38	180	38
2	20	180	18.4	180	18.4
3	25	180	22	180	22
4	60	180	57.8	180	57.8
5	44	180	44.2	180	44.2
6	45	180	43.2	180	43.2
7	60	180	57.8	180	57.8
8	70	223	60.95	180	74.2
9	35	180	31.8	180	31.8
10	55	180	59.6	180	59.6
11	48	180	46.4	180	46.4
12	30	180	27.4	180	27.4
13	65	197	60.95	180	66
14	45	180	43.2	180	43.2
15	25	180	22	180	22
16	100	321	60.95	180	108.8
17	95	291	60.95	330	47.8
18	120	358	60.95	430	35.2
19	115	340	60.95	430	29.5
20	140	430	60.95	430	60.9
Sum		4500.00	938.45	4500.00	934.20
Standard Deviation			15.48		21.46

CHAPTER 3: OPTIMAL NETWORK-LEVEL MOBILITY AND CAPACITY EXPANSION DECISIONS

INTRODUCTION

The ultimate goal of transportation infrastructure planners is to provide the best possible level of service to the network users. Major contributing factors defining the level of service are user travel time from an origin to destination, the quality of pavement condition and network safety. In the last chapter, pavement rehabilitation policies to guarantee certain level of pavement quality were discussed. In this chapter, network mobility improvement consideration during capacity expansion is discussed. The goal of, adding new capacity to the network is to improve the travel times along origin destination routs and mitigate congestion. Any change in network condition (either change in capacity or considerable change in pavement condition) will change the driver's route choice or user equilibrium.

Assuming the availability of traffic information, drivers choose a path that minimizes their travel time from an origin to destination. Increasing link capacity will improve travel time that can be translated in user cost saving by considering the intrinsic value of time. The agency resources can be allocated to maintain and/or improve the current pavement quality or resources can be use to expand the network and simultaneously improve mobility and safety. The objective of this chapter is to build and solve an optimization model to allocate resources for maximum mobility under uncertainty in network travel demand.

NETWORK DESIGN PROBLEM

Network design problem (NDP) is the problem of finding optimal network expansion decisions for a given network of transportation. In urban transportation networks, the path travel times are dependent on path flows. Given multiple available paths that users can take, they take the shortest path from the origin to the destination. However, when user flow in any given path exceeds a threshold, users start considering other paths to their destination. The travel time on each link changes with the flow and therefore, the travel time on several of the network paths changes as the link flow change. A stable condition is reached only when no traveler can improve his travel time by unilaterally changing routs.

The user equilibrium (UE) problem is looking to find the distribution of users among the possible paths. NDP is formulated in a bilevel mathematical program framework where the upper level is the minimization of the total system travel time and the lower level is the UE problem. In traditional NDP, the travel demand between source and destination is assumed to be certain. However, transportation networks are characterized by uncertainty. A robust network design problem should consider risk associated with the uncertainty in the travel demand.

While user equilibrium solution is the best representation of traffic flow, the system optimal traffic flow that represents the system's minimum total traffic flow can also be used to determine traffic flow. In a network without congestion, the UE and SO solutions are equal. However, it is proven that in the worst case scenario the user equilibrium solution can be twice as bad as of the system optimal solution. For comparison between system optimal and user optimal solution refer to LaBlanc and Abdulla *(23).* User Equilibrium Network Design Problem is (UENDP) is computationally hard to solve. However, a number of heuristic algorithms are suggested to solve the UENDP to reduce the computational complexity *(24*). An alternative for UENDP is the system optimal network design problem in which the solution represents optimal flow and expansion decisions such that the system total travel time is minimized. Patil and Ukkusuri *(25)* have compared the SONDP and UENDP and shown that the solution gap between the social cost of UENDP and SONDP is about 5% and the small difference justifies use of SONDP. Model in (14)-(14c) is the user equilibrium problem formulation.

TRAVEL DEMAND UNCERTAINTY

Forecasting the travel demand for any given O-D pair requires careful consideration of different factors like demographic, time of the day, etc. In most of the works in the literature on NDP travel demand for O-D pairs are assumed deterministic. Demand on transportation networks depends on various uncertain factors and for robust network-level decision making, the uncertainty in the travel demand should be taken into consideration. To guarantee the robustness of the solution, using a risk measure that appropriately reflects the uncertainly in travel demand is suggested.

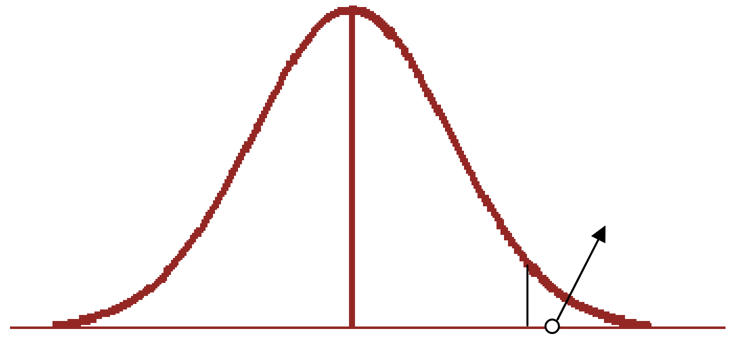

FIGURE 7 Travel demand under

To address the uncertainty in the travel demand for the origin destination pairs, is introduced in the NDP to represent the risk associated with travel demand uncertainty between O-D pairs in the SONDP problem. is defined as the average travel demand in percent of worst case demand scenarios. Figure (7) depicts

Notation and Model Formulation

The following notations are used in the rest of this report.

Sets

N set of nodes

A set of arcs

R set of origin nodes

S set of destination nodes

k_{rs} set of paths connecting O-D pair r-s

Parameters

Flow on path k connecting O-D pair r-s;

c_k^{rs} Travel time on path k connecting pair r-s;

$q_{rs}^{\beta-CVaR}$ Trip rate between origin r and destination s under $\beta - CVaR$ level;

$\delta_{j,k}^{rs}$ Indicator variable 1 if link a is on path k between O-D pair r-s, 0 otherwise;

l, u Lower and upper bounds on link expansion

K_a Link capacity

T_a Link performance function parameter

θ_a Dual of expansion cost

Decision Variables

x_a Flow on link j ; v = (…,v_j,…)

t_a Travel time on link a; t = (…,t_j,..)

y_a Continous link expansion variable

LINK PERFORMANCE FUNCTION

The level of service offered by transportation network is a function of the usage of the network. Due to congestion, the travel time on network links is an increasing function of flow. As a result, a link performance function rather than a constant travel time measure should be associated with each of the links representing the network. The performance function relates the travel time on each link to the traversing this link. The Bureau of Public Roads (BPR) link cost function is used in this study. For a given link a, we have:

$$c_a(x_a, y_a) = T_a^0 + \beta_a \left(\frac{x_a}{K_a + y_a}\right)^{\alpha}$$

USER EQUILIBRIUM

$$z(\mathbf{x}) = \text{Min} \sum_a \int_0^{x_a} t_a(w)\, dw \tag{14}$$

Subject to

$$\sum_k f_k^{rs} = q_{rs} \qquad \forall\, r, s \tag{14a}$$

$$f_k^{rs} \geq 0 \tag{14c}$$

USER EQUILIBRIUM NETWORK DESIGN PROBLEM (UENDP)

$$\text{Min} \sum_a x_a c_a(x_a, y_a) \; + \sum_a \theta_a y_a \tag{15}$$

Subject to

$$l \leq \; y_a \leq u \tag{15a}$$

$$x \in X \; is \; USER \; Equlibrium \tag{15b}$$

$$\boldsymbol{X} = argmin\; z(\mathbf{x})$$

SYSTEM OPTIMAL NETWORK DESIGN PROBLEM (SONDP)

Formulation (16)-(16c) is the modified SONDP with $\beta - CVaR$ on travel demand:

$$\text{Min} \sum_a x_a c_a(x_a, y_a) \; + \sum_a \theta_a y_a \tag{16}$$

Subject to

$$\sum_k f_k^{rs} = q_{rs}^{\beta-CVaR} \quad \forall\, r, s \tag{16a}$$

$$x_a = \sum_r \sum_s \sum_k f_k^{rs} \delta_{a,k}^{rs} \quad \forall\, a \in \mathrm{A} \tag{16b}$$

$$l \leq y_a \leq u, \qquad f_k^{rs} \geq 0 \tag{16c}$$

The biggest advantage of the SONDP formulation lies in its convexity property. The convexity proof is straightforward: the objective function is concave assuming linear link improvement cost function and constraints are all linear. The model can be solved to optimality by existing global non-linear solvers like MINOS. The SONDP formulation is the best candidate to expand the NDP to enhance safety and mobility. It provides flexibility in terms of adding new decision variables and/or constraints to the model as long as the convexity of the model is intact.

Test Network

To demonstrate the approach described here, the following test network taken from literature is used. The transportation network in Figure (8) has two O-D pairs (1,6), (6,1) with 16 links over 16 paths, of which 8 links are considered for expansion. The travel demand for origin destinations of (1,6), (6,1) are uncertain and normally distributed with $N(\mu_1, \sigma_1)$, $N(\mu_2, \sigma_2)$ respectively. The links that are considered for expansion are (1,3), (2,1), (3,2), (3,5), (5,6), (6,4), and (6,5). Figure (8) shows the network configuration, and link-specific data is displayed in table 4. In order to compare our results with optimal UENDP that is reported in literature, $q_{(1,6)}^{\beta-CVaR}$, $q_{(6,1)}^{\beta-CVaR}$ are assumed to be equal to 20 and 10, respectively.

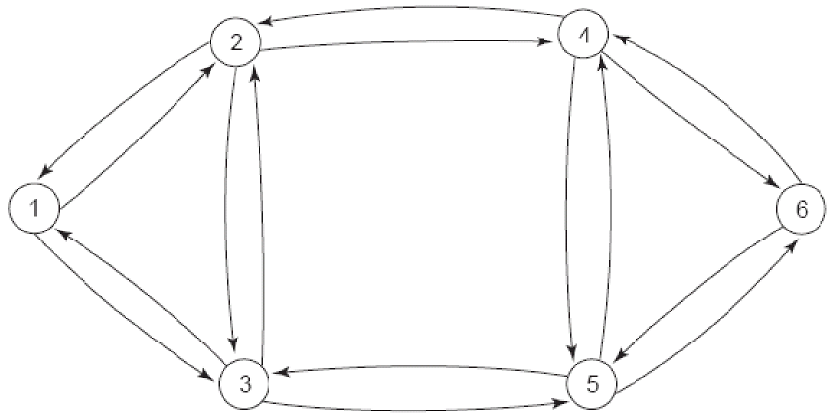

FIGURE 8 Transportation Network

TABLE 4 Data for the Test Network

	Arc (a)	T_a	β_a	K_a	θ_a
1	(1,2)	1.0	10.0	3.0	2.0
2	(1,3)	2.0	5.0	10.0	3.0
3	(2,1)	3.0	3.0	9.0	5.0
4	(2,3)	4.0	20.0	4.0	4.0
5	(2,4)	5.0	50.0	3.0	9.0
6	(3,1)	2.0	20.0	2.0	1.0
7	(3,2)	1.0	10.0	1.0	4.0
8	(3,5)	1.0	1.0	10.0	3.0
9	(4,2)	2.0	8.0	45.0	2.0
10	(4,5)	3.0	3.0	3.0	5.0
11	(4,6)	9.0	2.0	2.0	6.0
12	(5,3)	4.0	10.0	6.0	8.0
13	(5,4)	4.0	25.0	44.0	5.0
14	(5,6)	2.0	33.0	20.0	3.0
15	(6,4)	5.0	5.0	1.0	6.0
16	(6,5)	6.0	1.0	4.5	1.0

SONDP WITH MINIMUM PATH TRAVEL TIME

As mentioned before, mobility is one of the major network quality indicators. If the travel time between O-D pairs is taken as the network mobility indicator, the goal of transportation planners is to decrease the travel time between O-D pairs for all users traveling on different paths over the same O-D pair. To enhance mobility in the network during network expansion decisions, a new decision variable is introduced to the model. TT_{rs}^{k} parameter is defined as the total travel time over all paths $k \in K$ that connect the same O-D pair of rs; $r \in R$, $s \in S$. Formulation (17)-(17d) is a modification of SONDP that yield the lowest travel time for all paths connection the same origin and destination.

$$\text{Min} \sum_{a} x_a c_a(x_a, y_a) \;+ \sum_{a} \theta_a y_a \;+ \sum_{r}\sum_{s} TT_{rs} \tag{17}$$

Subject to

$$\sum_{k} f_k^{rs} = q_{rs}^{\beta-CVaR} \quad \forall\, r, s \tag{17a}$$

$$x_a = \sum_{r}\sum_{s}\sum_{k} f_k^{rs}\delta_{a,k}^{rs} \quad \forall\, a \in \mathrm{A} \tag{17b}$$

$$\sum_{a} c_a(x_a, y_a)\delta_{a,k}^{rs} \quad \le TT_{rs}^{k} \quad \forall\, r \in R, s \in S\,, k \in K \tag{17c}$$

$$l \le\; y_a \le u\,, \qquad f_k^{rs} \ge 0 \tag{17d}$$

The model minimizes the upper bound on the travel time for all paths connecting the same origin and destination. The goal of the model is to seek capacity expansion decisions under both minimum expansion cost and travel time for O-D pairs. The solution to the model will decrease the travel time and hence increase network overall mobility over O-D pairs with the smallest possible expansion cost. The TT_{rs}^{k} can be used as the basis for other strategic decisions. The benefit of this solution will become more evident when in the next model TT_{rs}^{k} are treated as a parameter to the model that solves for optimal expansion decisions that satisfies a constant TT_{rs}^{k} with restriction on link capacity expansion.

SONDP WITH CONSTANT PATH TRAVEL TIME

In the model (18)-(18d), the travel time between any origin and destination pair is considered as a given parameter and the model is solved to determine the required expansion on each link that is considered for expansion to achieve the required TT_{rs}^{k} . The solution from the previous model is essential in setting the TT_{rs}^{k} parameter for this model since the model in general is very sensitive to the parameter and unrealistic TT_{rs}^{k} values would make it infeasible. In the numerical example, the model is solved to determine capacity expansion required to equalize the travel time between the two origin and destinations.

$$\text{Min} \sum_{a} x_a c_a(x_a, y_a) \quad + \sum_{a} \theta_a y_a \tag{18}$$

Subject to

$$\sum_{k} f_k^{rs} = q_{rs}^{\beta-CVaR} \qquad \forall\, r, s \tag{18a}$$

$$x_a = \sum_{r}\sum_{s}\sum_{k} f_k^{rs} \delta_{a,k}^{rs} \quad \forall\, a \in \text{A} \tag{18b}$$

$$\sum_{a} c_a(x_a, y_a)\delta_{a,k}^{rs} \quad \leq TT_{rs}^{k} \qquad \forall\, r \in R, s \in S\,, k \in K \tag{18c}$$

$$f_k^{rs} \geq 0 \tag{18d}$$

The results of the model would provide transportation planners with the information on how link capacity expansion cost and travel times are related. The model is very sensitive to the TT_{rs}^{k} values and it becomes infeasible if TT_{rs}^{k} parameters are not carefully selected. As mentioned before, the system optimal minimum travel time solution from the previous model can be used as a basis to check the sensitivity of the capacity expansion cost to different TT_{rs}^{k} values. Results from the three formulations are summarized in table (5). The first column is the solution reported in literature as the exact solution for the UENDP *(24)*. To compare the results generated by any version of SONDP with the optimal UENDP, the SONDP solution is solved by UE algorithm to find the social cost of the expansion decisions. Figure 9a and 9b shows the travel time and cost for each model.

TABLE 5: Results

	UENDP	SONDP		SONDP-VTT[1]		SONDP-CTT[2]	
	Y	X	Y	X	Y	X	Y
1	0	1.139	0.000	1.020	0.000	0.225	0.000
2	4.61	8.861	2.950	8.980	3.124	9.775	4.300
3	9.86	14.713	8.528	14.936	9.026	16.898	12.848
4	0	1.386	0.000	1.223	0.000	0.000	0.000
5	0	1.039	0.000	1.020	0.000	0.375	0.000
6	7.71	5.287	10.699	5.064	10.166	3.102	5.710
7	0	0.000	0.000	0.000	0.000	0.150	0.000
8	0.59	8.961	0.000	8.980	0.000	9.625	19.927
9	0	16.000	0.000	16.159	0.000	16.898	0.000
10	0	0.000	0.000	0.000	0.000	0.216	0.000
11	0	1.039	0.000	1.020	0.000	0.159	0.000
12	0	4.000	0.000	3.841	0.000	3.102	0.000
13	0	15.237	0.000	15.528	0.000	5.359	0.000
14	1.32	8.961	0.000	8.980	0.000	9.841	0.964
15	19.14	0.762	0.000	0.631	0.000	11.539	15.426
16	0.85	19.238	20	19.369	20	8.461	6.858
O-D Travel Time		O-D (1,6): 20.64[3] O-D (6,1): 21.20		O-D (1,6): 20.48 O-D (6,1): 19.88		O-D (1,6): 19 O-D (6,1): 19	
SO Cost	N/A	508.98		509.61[4]		599.02	
UE Cost	557.14	527.792		526.42		633.64	

X: Flow Variable; Y: Expansion Variable

[1] System optimal network design problem with variable origin-destination travel time
[2] System optimal network design problem with constant origin-destination travel time
[3] Maximum travel time over all paths connecting the O-D pair.
[4] 549.97- 40.36 (TT1+TT2) = 509.61

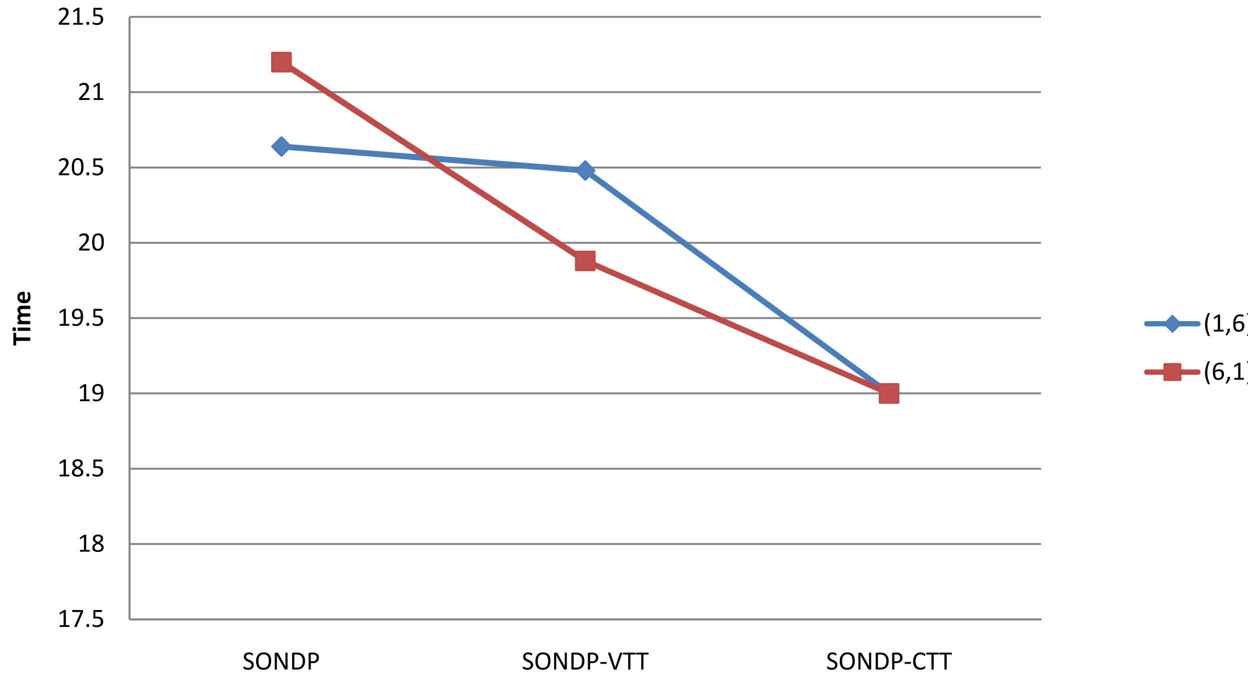

FIGURE 9-a O-D Travel Time for SONDP, SONDP-VTT and SONDP-CTT

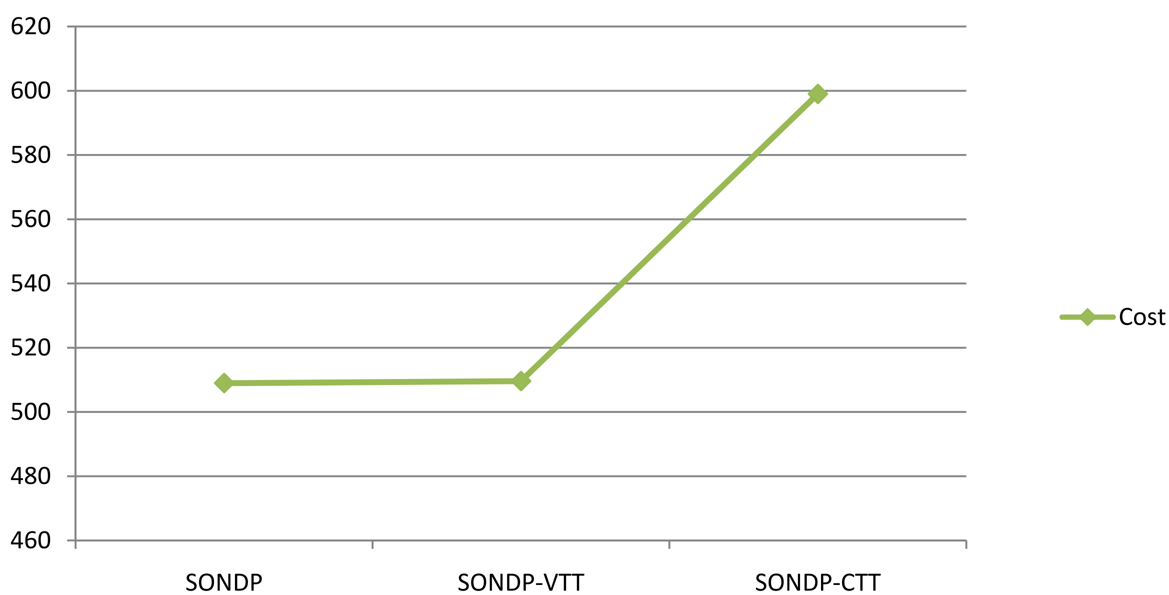

FIGURE 9-b Total Cost for SONDP, SONDP-VTT and SONDP-CTT

CHAPTER 4: OPTIMAL NETWORK-LEVEL SAFETY AND CAPACITY EXPANSION DECISIONS

INTRODUCTION

Traffic safety is one of the network's quality measures that often time is not taken into consideration when network intervention decisions are made. Network capacity expansion and reconstruction provide an excellent opportunity to improving overall safety levels. The goal of this chapter is to expand the SONDP to include network safety enhancement. Safety can be defined in terms of the rate of accidents that will result in passenger injury or property damage. Since capacity expansion decisions directly influence the network flow, the relationship between safety enhancement and network flow or flow to capacity ratio can is required to include safety enhancement in capacity expansion decisions.

NETWORK FLOW AND SAFETY

Figure (10) shows the relationship between accident rate and network flow and speed standard deviation. Garber and Ehrart *(26)* ran regression analysis on different factors affecting accident rate and showed a strong connection between speed variation and accident rate. It also shows that lower flow per lane plays a modest role in accident reduction. It is logical to assume that higher flow would automatically translate to lower speed variation. Figure (11) by Zhou and Sisiopiku *(27)* shows the accident rate with respect to the ratio of flow to the link capacity in a highway segment for PDO (property damage only) accidents and injury and fatal accidents. This relationship would better serve this analysis since in SONDP model that is considered for link expansion decisions; flow/capacity is one of the main components.

Network safety enhancement can be achieved along with network capacity expansion by either minimizing PDO or injury accidents. Although, the two safety indicators (injury and PDO) can be combined and treated as a single safety measure, they have been studied separately in this analysis to show their effect on network flow.

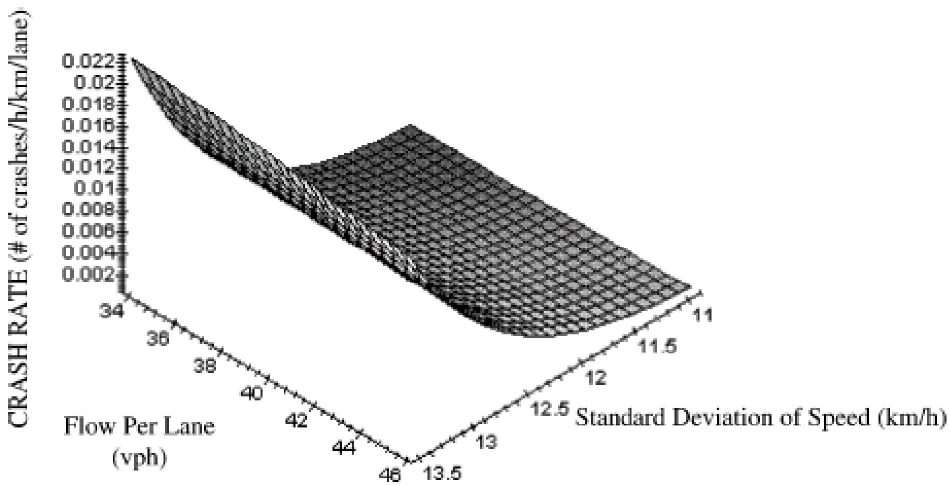

FIGURE 10 Crash Rate versus Standard Deviation of Speed and Flow per Lane

Source: Garber, N. J., Ehrhart, A.A. Effects of Speed, Flow and Geometric Characteristics on Crash Frequency for Two-Lane Highways *Transportation Research Record: Journal of the Transportation Research Board, No. 1981,* Transportation Research Board of the National Academies, Washington, D.C,2000.

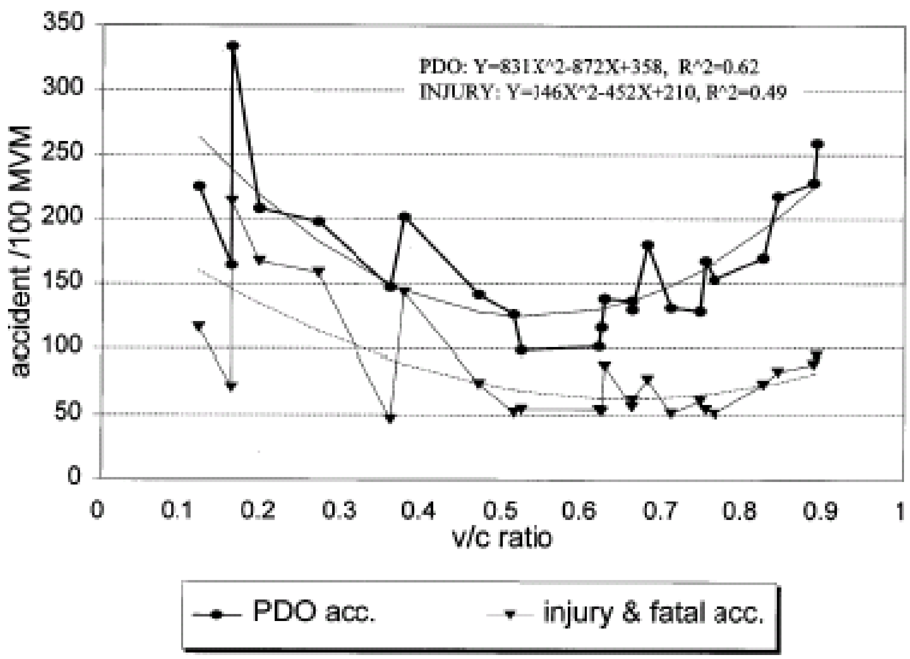

FIGURE 11 Accident rates v.s. v/c ratio for accidents involving injuries and fatalities and PDO accidents

Source: Patil, G. R, Ukkusuri, S. V. System- Optimal Stochastic Transportation Network Design In *Transportation Research Record: Journal of the Transportation Research Board, No. 2029,* Transportation Research Board of the National Academies, Washington, D.C, pages 80-86, 2007.

MINIMIZING PDO ACCIDENTS

As figure (11) shows, the relationship between total PDO accident rates and *v/c* (flow/capacity) ratio is a U-shaped function and PDO accidents are minimized when v/c ratio is in [0.5,0.6]. The formulation in (19)-(19c) is suggested to minimize the deviation from the minimum PDO rate when link expansion decisions are made

$$\text{Min} \sum_a x_a c_a(x_a, y_a) \; + \sum_a \theta_a y_a \; + \sum_a \left(\frac{x_a}{k_a + y_a} - .55\right)^2 \qquad (19)$$

Subject to

$$\sum_k f_k^{rs} = q_{rs}^{\beta-CVaR} \qquad \forall\, r, s \qquad (19a)$$

$$x_a = \sum_r \sum_s \sum_k f_k^{rs} \delta_{a,k}^{rs} \quad \forall\, a \in \mathrm{A} \qquad (19b)$$

$$l \leq \; y_a \leq u \qquad (19c)$$

$$f_k^{rs} \geq 0$$

The rates of accidents involving injury and fatality, however, have a slightly decreasing trend as *v/c* ratio increases and the lowest rate corresponds to high v/c ratios. The following model is suggested to minimize the injury accident in the network while considering link expansion decisions in the network. Table (6) summarizes the results from the model.

TABLE 6: PDO Reduction Model Result

	X	Y	$\frac{x_a}{k_a + y_a}$
1	1.16692	0	0.388974
2	8.83308	2.92124	0.683609
3	14.7134	8.54832	0.838451
4	1.40955	0	0.352387
5	1.04884	0	0.349613
6	5.2866	10.6776	0.417002
7	0	0	0
8	8.95116	0	0.895116
9	16.0049	0	0.355664
10	0	0	0
11	1.04884	0	0.52442
12	3.99513	0	0.665855
13	15.2459	0	0.346497
14	8.95116	0	0.447558
15	0.75898	0	0.75898
16	19.241	20	0.785348

MINIMIZING INJURY AND FATAL ACCIDENTS

The model in (20)-(20c) is formulated to minimize the injury accident in SONDP. Note that the model is set to maximize the sum of flow/capacity ratio for all links. Adding sum of ratios as a constraint will make the model infeasible due to flow restrictions and the only options is its addition to objective function. The computational results are reported in Table (7).

$$\text{Min} \sum_a x_a c_a(x_a, y_a) \; + \; \sum_a \theta_a y_a \; - \; \sum_a \frac{x_a}{c_a + y_a} \qquad (20)$$

Subject to

$$\sum_k f_k^{rs} = q_{rs}^{\beta-CVaR} \qquad \forall\, r, s \qquad (20a)$$

$$x_a = \sum_r \sum_s \sum_k f_k^{rs} \delta_{a,k}^{rs} \quad \forall\, a \in \text{A} \qquad (20b)$$

$$l \leq \ y_a \leq u$$

$$f_k^{rs} \geq 0 \qquad (20c)$$

TABLE 7: Injury Accident Rate Reduction Model Results

	X	Y	$\frac{x_a}{k_a + y_a}$
1	1.22076	0	0.40692
2	8.77924	2.7849	0.686688
3	14.6972	8.47609	0.840988
4	1.44285	0	0.360714
5	1.06996	0	0.356652
6	5.30282	10.656	0.418997
7	0	0	0
8	8.93004	0	0.893004
9	15.9892	0	0.355316
10	0	0	0
11	1.06996	0	0.534978
12	4.01077	0	0.668462
13	15.2019	0	0.345497
14	8.93004	0	0.446502
15	0.787368	0	0.787368
16	19.2126	20	0.784189

CHAPTER 5: SUMMARY AND CONCLUSIONS

Transportation networks are characterized by uncertainty that stems from different sources that should be taken into consideration during strategic decision making. Defining and using appropriate risk measures allows for robust decisions to be made whenever budget is restricted and/or network intervention actions are needed. This research covers methods of finding risk-averse rehabilitation decisions in a network of transportation infrastructure as well as optimal network-level safety and mobility enhancements during capacity expansion considerations.

In Chapter 2, risk-based rehabilitation decisions with emphasis on maintaining the network above a level of service define by risk are discussed. The long-term model is constructed based on the MDP framework to minimize the cost of network rehabilitation actions such that a certain pavement quality level is guaranteed. The risk-averse actions and transitional probabilities for the MDP model are constructed from the probability distribution of facility at the end of planning horizon. The result of the long-term model shows a gradual increase in rehabilitation intensity with increase in the roughness level. This approach can be extended to include the Bayesian updating of deterioration distribution function or parameters.

While developing long-term rehabilitation policies is important for transportation agencies, it is even more important to address the short-term network level rehabilitation policies when resources are not sufficient to implement the long-term optimal policies. Two short-term models that are used to make resource allocation decisions are presented: a Minimax model to minimize the highest CVaR over all facilities and a Knapsack model to minimize the total CVaR of all facilities subject to budget restrictions. The results from the two models show that the first model generates a solution with a lower variance across the network, but with slightly higher total quality level of roughness for all facilities, while the Knapsack model gives a solution with a high variance among the facilities, but with the total CVaR that is smaller compared to the first model. The magnitude of the difference between the total CVaR of the two solutions is significantly smaller than of the differences in their variance, hence implementing either model can be justified.

Transportation agencies can either chose to distribute their resources on the sole basis of cost/benefit ratios, or base the recourse allocation decisions on narrowing the gap among the quality level of facilities. Narrowing the quality gap can provide more consistency in pavement condition across the network with the slightly higher cost. Comparing the results from Minimax and Knapsack models clearly indicates the advantage of the Minimax model over the Knapsack model since the small cost saving that the Knapsack model offers does not justify the high variance in facility's quality level.

Safety and mobility are two major factors in defining the service quality level for users of transportation infrastructure. In Chapter 3, incorporating mobility, defined by minimum travel time over all paths connecting O-D pairs, into capacity expansion decisions is discussed. Three models are discussed to improve mobility in the network. SONDP that gives the system-optimal solution is based on the risk constraints on network travel demand; SONDP-VTT that minimizes the upper bound on all paths connecting the same O-D pair, and SONDP-CTT that takes the travel time on paths between O-D pairs as parameter and yields the optimal network capacity expansion decisions. The results of the models demonstrated how link capacity expansion cost and travel times are related. The computational results showed that including mobility enhancements would only slightly increase the total cost. The solution can also serve as the basis for further travel time reductions when budget restrictions are loose.

In Chapter 4, safety as an important network quality indicator is discussed and two models to enhance safety during capacity expansion decisions are outlined. Previous research on the effect of traffic flow on safety suggests that the relationship between total PDO and injury accident rates and *v/c* (flow/capacity) ratio is a U-shaped function, and PDO accidents are minimized when v/c ratio is in [0.5, 0.6]. Two models are presented to reduce accident rate by changing the ratio of flow to the link capacity in a highway segment for PDO (property damage only) accidents and injury and fatal accidents. Computational results suggested that the solution of two models is slightly different with improved flow to capacity ratio. The models can be extended to weight each factor and combine them into a single factor based on link characteristics.

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