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Optimization of Infrastructure Rehabilitation Funding Decisions Considering Vulnerability-Based Stochastic Deterioration Modelling

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ABSTRACT

Infrastructure increasing bill, due to failure to fill the investment gap between infrastructure needs and available funds, is still persistent. Many fund-allocation optimization models were developed to find a solution to this everlasting problem. However, the pace of these efforts is not compatible with the fast deterioration of infrastructure due to its vulnerability to exogenous factors that accelerate its deterioration beyond the expected rate. There is a lack of research efforts that have formulated infrastructure vulnerability in the prioritization and fund-allocation algorithm. Accordingly, this research proposes a fund-allocation optimization model that maximizes infrastructure physical performance under budget constraints, considering a new vulnerability-based stochastic deterioration modelling. The model computes first an overall vulnerability index, for each asset in the network, which is function of the attributing factors that may vary from one geographical location to another. The vulnerability index is then incorporated in a Markov-based deterioration behavior modelling to include the vulnerability impact in the fund-allocation algorithm. In this research, the proposed model is applied to a road network as one type of infrastructure to examine its performance. Thus, an empirical study was conducted to capture the exogenous factors that would make roads vulnerable to faster deterioration, including: excessive traffic loading, climate change, neighboring disturbance, etc. Applying the model and comparing it against the existing models, results demonstrated rationality behind the generated funding decisions using the proposed model, and the cumbersome consequences of ignoring vulnerability. Thus, the model can help policy-makers make realistic funding decisions to maintain infrastructure performance.

INTRODUCTION

Infrastructure is the main driver of any nation's economy. Failure to address infrastructure deterioration challenges, leads to huge losses. Among those challenges is the persistent investment gap between the accumulating infrastructure needs and the available funds (ASCE, 2016). This gap is due to the fast deterioration of infrastructure, the existence of hundreds of deteriorated assets competing for funds, and the slow pace of act towards this gap. The fast deterioration can be attributed to the vulnerability of infrastructure to exogenous factors that accelerate its deterioration beyond the expected rates. Therefore, to close this challenging investment gap, there is a need for an efficient fund-allocation model that considers the impact of infrastructure vulnerability on its rate of deterioration, when prioritizing the competing critical structures for funds.

Many research efforts developed fund-allocation optimization models using deterministic or stochastic deterioration models for different types of infrastructure networks. Examples include: roads (Saad et al., 2018), bridges (Bocchini and Frangopol, 2012), buildings (Rashedi and Hegazy, 2015), water and sewer networks (Atef at al. 2012). On the other hand, some research efforts have addressed infrastructure vulnerability to service disruption and failure, yet with more attention towards vulnerability to disasters like terrorist attacks and floods (Dehghani et al., 2014). Among those efforts, Nourzad and Pradhan (2015) developed a framework to assess road transportation networks vulnerability to artificial and natural disruptions. The model utilizes a clustering algorithm to classify critical road links, considering the timing and severity of the disruption. Dehghani et al. (2014) developed a condition-based algorithm to determine the roads vulnerability to disruptions and failures using two types of performance measures: vehicle miles travelled and network efficiency. Bell at al. (2008) developed a game theoretic approach to analyze the roads vulnerability to disruption, attacks, or failure, and to determine the optimum solution that minimizes the associated loss. Ezell (2007) developed a value model to quantity the vulnerability of clear water systems to risk scenarios using protection measures of deterrence, detection, delay and response. Despite the existing research efforts, none has considered the accelerated deterioration of infrastructure due to its vulnerability in the fund-allocation mechanism. Accordingly this research proposes a network-level fund-allocation optimization model that formulates infrastructure vulnerability in the deterioration behaviour modelling.

In this paper, the research has been narrowed to focus on roads and highways infrastructure networks, as they are one of the most critical infrastructure networks. Many research efforts have studied the deterioration factors of roads and highways to properly design the road and determine its expected life. Among those factors are: traffic (volume, type, speed, repetition, axle spacing), pavement age, environment (aggressive chloride invasion, temperature, and moisture), construction, pavement structure, and maintenance activities (Haas et al. 2015, Sabatino et al. 2015). However, roads are often exposed to exogenous factors that can potentially aggravate those deterioration factors, and thus making them vulnerable to faster degradation.

Therefore, in this research, an empirical study has been conducted to capture those exogenous factors, and embed their impact in the deterioration behaviour modelling to be taken into account in the fund-allocation algorithm. Accordingly, the paper first presents the framework of the proposed optimization model. Then, it explains the vulnerability assessment of roads followed by the formulation of the asset's vulnerability in the deterioration behaviour modelling, and the mathematical formulation of the optimization model considering the vulnerability-based deterioration behaviour modelling. Afterwards, it shows the application of the model to a case study to examine its performance and compare it against the existing optimization models that ignores the impact of infrastructure vulnerability.

FRAMEWORK OF THE PROPOSED OPTIMIZATION MODEL

This research proposes a network-level fund-allocation optimization model that prioritizes competing roads for repair under limited funds, considering the vulnerability of roads to accelerated deterioration behind the expected rates. Accordingly, as shown in Figure 1, vulnerability assessment is carried out simultaneously with the condition assessment to be used as an input to the deterioration behavior modelling. Once the vulnerability impact is embedded in the deterioration behavior, LCCA will be conducted to determine the most cost-effective intervention type. Afterwards, an optimization algorithm will be used to prioritize the competing roads for repair over a pre-defined funding period, in order to arrive at the optimum network performance under the imposed budget constraints.

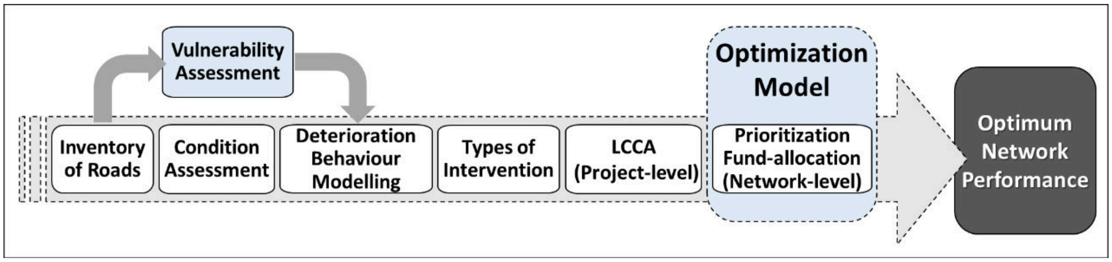

Figure 1. Framework of the proposed fund-allocation optimization model

VULNERABILITY ASSESSMENT

Road vulnerability, in this research, is the exposure of road to exogenous factors that contribute to accelerating its deterioration, as illustrated in Figure 2. The vulnerability of each road depends on its characteristics, including: geographical location, type, traffic demand, etc. Therefore, it is important to first capture all the potential factors that may contribute to the road's vulnerability, and then evaluate the vulnerability degree (High, medium, low, etc.) of each road with respect to those factors. In an effort to capture those exogenous factors, brainstorming sessions and surveys with experts were conducted along with extensive literature review. The factors are classified in this research according to three categories: 1) Traffic loading, 2) Environment, and 3) Neighboring Disruption.

The "Traffic loading" related factors are the ones that can potentially increase the loading beyond the estimated limits considered in the pavement design. Among those factors are: traffic overloading, traffic congestion, traffic overflow. However, it is important to identify the aspects that contribute to those factors. For example, the lack of load restriction and law enforcement increases the number of incidents of overweight moving trucks. Although traffic congestion may actually decrease the traffic flow, however, it decreases the designed axle spacing between successive vehicles due to closely spaced congested vehicles which can be more critical for large span highway bridges (Caprani, 2012). Congestion can be caused by traffic bottlenecks due to user driving behavior, accidents, etc. On the other hand, traffic overflow can be attributed to changes in land use due to demographic changes, ineffective traffic management systems, absence of alternative underground means of transportation between two nodes, improper mass transportation means leading to high reliance on passenger vehicles, reduction in road capacity leading to traffic overflow per lane, etc.

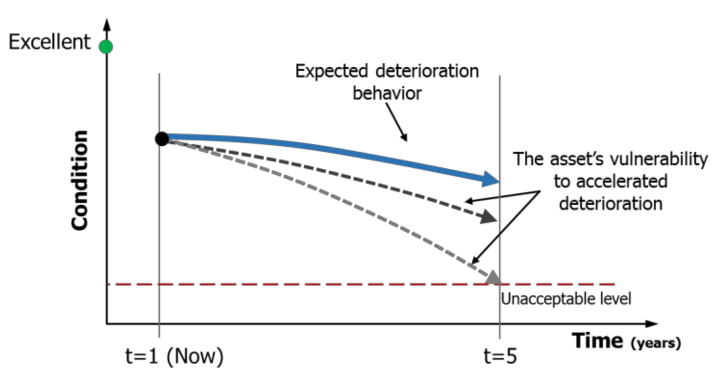

Figure 2. Impact of asset's vulnerability on the deterioration behavior

The "Environment" related factors are more concerned with the global climate change impact which varies from one country to another. For instance, in Egypt, the roads are vulnerable to fast deterioration due to unexpected heavy rainfalls and improper drainage systems, and due to very high temperatures and sun radiation as a result of the heat waves that Egypt has witnessed lately. The "Neighboring Disruption" related factors are mainly concerned with disruption caused by co-located assets, including: leakage from aging underground water pipelines, uncoordinated utility works (e.g., multiple cut and cover to install or repair underground utilities which expose the road to hazards), water intrusion due to excessive landscape irrigation, etc.

Currently in this research, the vulnerability Vf_i of each road segment *i* with respect to each factor (*f*) is qualitatively assessed using a percentage value from 0% to 100%. Where, 0% means no vulnerability and 100% means highest degree of vulnerability. Afterwards, an overall weighted vulnerability index V_i is computed for each road segment to determine the level of vulnerability of the road relatively to the other roads in the network. Accordingly, V_i of each road is computed as follows:

$$V_i = \sum_{f=1}^{F} W_f \times Vf_i \tag{1}$$

Where, W_f is the relative weight of influence of each vulnerability factor (*f*), *F* is the number of vulnerability factors.

VULNERABILITY-BASED DETERIORATION BEHAVIOR MODELLING

In this paper, Markov chain technique has been adopted to account for the uncertainty associated with the deterioration behavior. In the literature, Markov chain has been widely used in infrastructure stochastic deterioration modelling. There are several variations of Markov chain process, including: time-based versus state-based condition change over time, homogeneous versus non-homogenous transition probabilities change over time (Moreira et al. 2016). In this paper, it has been assumed that the condition of the road will only change after a fixed interval of time using a constant probability transition matrix over the analysis period, due to the difficulty of getting timely real data. Accordingly, state-based homogeneous Markov process has been utilized. For (*m)* condition states, the probability transition matrix (Pv_i) for any given road segment (*i*) considering vulnerability, is defined as follows:

$$Pv_i = \begin{bmatrix} Pv_{i,1,1} & Pv_{i,1,2} & Pv_{i,1,3} & Pv_{i,1,k} & Pv_{i,1,m} \\ Pv_{i,2,1} & Pv_{i,2,2} & Pv_{i,2,3} & Pv_{i,2,k} & Pv_{i,2,m} \\ Pv_{i,3,1} & Pv_{i,3,2} & Pv_{i,3,3} & Pv_{i,3,k} & Pv_{i,3,m} \\ Pv_{i,j,1} & Pv_{i,j,2} & Pv_{i,j,3} & Pv_{i,j,k} & Pv_{i,4,m} \\ Pv_{i,m,1} & Pv_{i,m,2} & Pv_{i,m,3} & Pv_{i,m,4} & Pv_{i,m,m} \end{bmatrix} \tag{2}$$

Where, $Pv_{i,j,k}$ is the probability of transition of road segment (*i*) from condition state (*j*) to state (*k*) after constant transition time (e.g., 1 year of the funding period), considering vulnerability. The sum of the probabilities in each row must be equal to one, as shown in Equation 3. Each probability of transition ($Pv_{i,j,k}$), considering vulnerability, is computed empirically using Equation 4.

$$\sum_{k=1}^{m} Pv_{i,j,k} = 1 \quad for\ j = 1,2,3,\ldots m\, states, i = 1,2,3,\ldots n\, assets \tag{3}$$

$$Pv_{i,j,k} = P_{i,j,k} \times (1 - V_i) + P_{i,j,k-1} \times V_i \quad (4)$$

Where, $P_{i,j,k}$ is the typical transition probability of each road i from condition state j to state k after constant transition time (Moreira et al. 2016), and V_i is an overall weighted vulnerability index computed for each road i, as previously mentioned.

In the developed model, the current condition of the road segment is measured using a performance index, then based on its value, it will be rated according to pre-defined m condition states with pre-defined upper and lower limits. In this paper, 5 condition states are defined (m = 5): very good, good, fair, poor, and very poor. To allow modelling the deterioration behaviour using Markov chain, an initial condition vector ($1 \times m$) is constructed as shown in Equation 5. The sum of the percentages in all condition states must be equal to one, as shown in Equation 6. However, once the performance index value satisfies the upper and lower limits of a certain state, then it will be assigned a value of 100% in this condition state.

$$CR(0)_i = \begin{bmatrix} CR_i^1 & CR_i^2 & CR_i^3 & CR_i^4 & CR_i^s \end{bmatrix} \quad (5)$$

$$\sum_{s=1}^{m} CR_i^s = 1 \quad for\, i = 1,2,3,\ldots n\, assets \quad (6)$$

Where, $CR(0)_i$ is the condition rating of road asset i at time t = 0 (i.e., present time), CR_i^s is the percentage of the road i in a certain condition state S (S = 1, 2, 3 … m). Accordingly, the probability of having the road condition in a certain state k after t years without intervention, $CR(t)_i|_{wo}$, can be computed by multiplying the current condition rating by the probability transition matrix after t years which is computed by multiplying the matrix Pv_i by itself t times (baik, 2006), as follows:

$$CR(t)_i|_{wo} = CR(0)_i^T \times (Pv_i)^t \quad (7)$$

Where $CR(t)_i|_{wo}$ is the future condition vector ($1 \times m$) after t years without intervention, and $CR(0)_i^T$ is the transpose of the current condition rating vector presented in Equation 5. To determine the expected condition rating after t years without intervention, each condition state will be represented by a score S from 1 to 5, where 1 represents the best condition state (very good), and 5 represents the worst condition state (very poor). Therefore the expected condition rating $ECR(t)_i|_{wo}$, without intervention, after t transitions can be computed by multiplying the future condition vector $CR(t)_i|_{wo}$ with the condition state vector S= [1 2 3 4 5], as follows:

$$ECR(t)_i|_{wo} = CR(t)_i|_{wo} \times S \quad (8)$$

Based on the intervention policy, the future condition vector with interruption, $CR(t)_i$, can be determined as discussed later, and accordingly, the expected condition rating after intervention $ECR(t)_i|_w$ will be computed using Equation 8.

MATHEMATICAL FORMULATION OF THE OPTIMIZATION MODEL

The optimization model is developed to determine which assets to repair and the optimum repair timing within the specified funding period, while maximizing the overall performance of the road network. In this decision making problem, there are multiple combinations of assets and repair timings. Thus, to solve this combinatorial problem, a typical linear integer programming optimization model has been developed with a single objective function of maximizing the overall performance of the road network. The model is generic enough to accommodate any type of infrastructure. In the model, a binary decision variable x_{it} has been utilized to represent the 2-dimensional solution space of n assets (i = 1 to n assets) and T years (t = 1 to T years of the fund period). If x_{it} =1, it means that asset i will be repaired in year t in the funding period; while, if x_{it} =0, it means that asset i will not be repaired in this funding period.

The objective function is to maximize the overall performance of the road network (P_{Net}). Therefore, it has been formulated to maximize the weighted sum of the condition improvement gained by each asset i, as follows:

$$\text{Maximize } P_{Net} = \sum_{i=1}^{n} \sum_{i=1}^{T} x_{it} \times IE_{it} \times RIF_i \tag{9}$$

$$IE_{it} = ECR(t)_i\,|_{wo} - ECR(t)_i\,|_{w} \tag{10}$$

Where, RIF_i is the relative importance factor of asset i with respect to the other assets in the network, IE_{it} is the improvement effect gained by asset i if it is repaired in year t, $ECR(t)_i\,|_{wo}$ is the expected condition rating of the asset after t years without intervention based on Markov chain as shown in Equation 8, while $ECR(t)_i\,|_{w}$ is the expected condition rating of the asset after t years with intervention at year t.

The constraints of the optimization model are: 1) each asset i can only be visited once for intervention during the funding period, as formulated in Equation 11, 2) the total annual intervention costs TC_t in any given year t should not exceed the available annual budget B_t in this year as formulated in Equation 12.

$$\sum_{t=1}^{T} x_{it} \leq 1 \quad for\, i = 1,2,3,\ldots to\, n\, assets \tag{11}$$

$$TC_t = \sum_{i=1}^{n} x_{it} \times EIC_{it} \leq B_t \quad for\, t = 1,2,3\ldots T\ years \tag{12}$$

$$EIC_{it} = CR(t)_i \times C \times A_i \tag{13}$$

Where, EIC_{it} is the expected intervention cost of asset i at year t, which depends on the probable condition state $CR(t)_i$ of the asset with intervention after t years, the area A_i of the asset, and the intervention cost per road area C , [$C^1\, C^2\, C^3\, C^4\, C^s$], corresponding to each state S (S = *1, 2, 3, … m*), as formulated in Equation 13.

CASE STUDY APPLICATION

To test the proposed optimization model considering the new vulnerability formulation in the deterioration behavior, a case study for a road network has been utilized. The road network is located in Egypt, it includes 5 different roads: two urban roads (Corniche and Shehab) and three highways (Saft, Ring road, Cairo-Alex), consisting of 50 segments with a total length of 34.5 Km and area of 544,000 square meter. Since there is an absence of up-to-date data regarding the current condition of the roads, "Roadroid" smartphone application has been utilized to facilitate collecting data about the roads' condition. This application allows measuring the road condition in terms of the international roughness index (IRI) (Forslof, 2014). In this case study, the funding period is assumed 5 years with an annual budget of 10 million EGP. An intervention policy is assumed as well; such that, no intervention would be required for roads in "very good" or "good" condition. As a result, 3 types of treatments are identified for "Fair", "Poor", and "Very poor" condition states, respectively.

To allow modelling the deterioration behavior using Markov chain, the road performance is rated using IRI, and then assigned a condition state category (e.g., "Good" category) based on the IRI value ranges shown in Table 1 (based on Haas et al. 2015). Based on that, an initial condition rating $CR(0)_i$ vector is generated (as shown in Equation 5) for each road. In addition, an integer score S out of 5 is assigned based on the condition state category that it belongs to it, as shown in 3rd column of Table 1. Accordingly, the expected condition rating without intervention $ECR(t)_i|_{wo}$ for each road segment i at any given repair year t, is computed using Equation 8.

Table 1. IRI Categories and Score Values

IRI Value	Condition State Category	Score S
IRI ≤ 1	Very Good	1
$1 <$ IRI ≤ 1.5	Good	2
$1.5 <$ IRI ≤ 2	Fair	3
$2 <$ IRI ≤ 2.5	Poor	4
IRI > 2.5	Very Poor	5

In this paper, it is assumed that the asset's condition after repair will be very good. Accordingly, the percentage of any road segment i in a certain condition state S without intervention, will be transferred to a very good state once an intervention takes place. For instance, if an asset has $CR(t)_i|_{wo}$ = [0% 30% 25% 25% 20%], then its $CR(t)_i$ after intervention is 70% in "very good" state, 30% in "good" state, and 0% in the remaining states (i.e., $CR(t)_i$ = [70% 30% 0% 0% 0%]. Accordingly, the expected CR after intervention $ECR(t)_i|_w$ and the improvement effect IE_{it}, for each road segment, are computed, as formulated in Equations 8 and 10. Following the assumed intervention policy, the intervention costs C^1 and C^2 which correspond to "very good" and "good" states are assigned zero values in Equation 13.

For the road network under study, 12 potential vulnerability factors are identified and classified according to three already identified criteria. However, they can be extended as per any further studies. Table 2 shows the value of each vulnerability factor Vf_i in each road, and the relative weight of influence W_f of each factor. As shown in the table, the impact of each vulnerability factor differs from one road to another according to the road characteristics, as previously discussed. For instance, the road capacity reduction has higher impact on roads 1 and 2, as they are located in the center of the city where there is lack of designated parking areas and bus stops, and ineffective law enforcement to prevent unauthorized parking and stops. Also, land use change has higher impact on roads 1 and 2, as the areas where those roads are located have partially changed over time to commercial areas due to congestion and migration of residents. Using the 12 factors, an overall vulnerability index V_i is computed for each road using Equation 1, followed by all the succeeding formulations.

Table 2. Value of Vulnerability Factors and Their Degree of Influence

Group	Vulnerability Factor Vf_i	Weight W_f	Road 1 (Corniche)	Road 2 (Shehab)	Road 3 (Saft)	Road 4 (Ring)	Road 5 (C-A)
CC	Exposure to high temperatures and radiation	8%	20%	20%	60%	75%	90%
	Heavy rainfall & lack of drainage systems	5%	80%	80%	50%	60%	20%
TOF	Absence of underground transportation means	5%	10%	75%	50%	80%	0%
	Improper mass transportation means	7%	20%	20%	85%	85%	40%
	Lack of road alternatives	5%	60%	70%	40%	75%	30%
	Reduction in road capacity: lack of parking areas & designated bus stops	15%	90%	90%	70%	60%	5%
TC	Change of land use	10%	70%	70%	20%	20%	20%
	Accidents	5%	5%	5%	65%	80%	10%
	User driving behavior	5%	70%	70%	70%	70%	10%
TOL	Movement of overweight vehicles	15%	30%	30%	75%	75%	0%
ND	Leakage from aging underground water pipe lines	10%	80%	80%	0%	0%	0%
	Uncoordinated utility works	10%	75%	75%	20%	20%	5%

CC: Climate change, TOF: Traffic overflow, TC: Traffic congestion, TOL: Traffic overload, ND: Neighboring disruption

To examine the performance of the proposed vulnerability-based fund-allocation optimization model against the existing models in the literature, two experiments have been conducted. In the first experiment, the proposed optimization model is applied to the case study. While in the second one, the vulnerability impact is excluded from the deterioration model (by setting the vulnerability V_i value in Equation 4 is set equal to zero) to resemble the already existing stochastic fund-allocation optimization models, and then applied to the case study. The optimization setup has been constructed in Microsoft Excel environment. Since, the road network case study used in this research is a small-scale one with relatively small solution space, Genetic Algorithms optimization technique has been utilized, using Evolver Excel Add-in.

Table 3 summarizes the key findings for both experiments. It can be noted from the table that the results of Exp-2, which overlooks the vulnerability impact, may look outperforming those of Exp-1 in terms of the overall network performance and number of roads repaired. However, these results may actually mislead decision makers. As, taking into consideration the vulnerability impact, has accelerated the deterioration behavior, and thus many segments ended up in “Very poor” condition state. This phenomenon can be observed in the large areas that Exp-1 has repaired in a “Very poor” condition as opposed to Exp-2 (Area of 101,443 m^2 vs. 88,560 m^2). Therefore, it costed much more to repair those segments, which in turn consumed from the budget available, and led to repairing less number of roads. Accordingly, this experimentation highlights the benefit of incorporating infrastructure vulnerability in the deterioration behavior to help decision makers set realistic funding strategic plans under budgetary constraints and to be aligned with the real infrastructure needs.

Table 3. Results Summary of the Optimization Experiments

Parameters		Exp-1 (With V_i)	Exp-2 (Without V_i)
Total Cost		EGP 49,020,378	EGP 49,590,675
Overall Network performance (P_{Net})		88.15	89.47
Number of selected road segments		34	37
Total Area Repaired (m^2)	F	57,446	61,748
	P	9,735	31,747
	VP	101,443	88,560
	Total	335,750	375,000

CONCLUSION

This paper presented a generic network-level fund-allocation optimization model with a new deterioration behavior formulation that considers the impact of infrastructure vulnerability to accelerated degradation. Markov chain model was adopted to simulate the assets' stochastic deterioration behavior. The mathematical formulations of embedding vulnerability in Markov chain process are presented, along with the formulations of the optimization model. To test the applicability of the model, a small-scale case study for a road network located in Egypt was utilized, and accordingly, vulnerability factors were identified. A comparative analysis was conducted to compare the proposed model against the existing fund-allocation models. From the results, the model proved its ability to arrive at realistic optimum funding decisions under budgetary constraints. Currently, there is on-going research on measuring the vulnerability factors quantitatively, enhancing the stochastic deterioration modelling to consider its dynamism over time, and further examining the model on large-scale case studies. In essence, this paper emphasizes the necessity of incorporating vulnerability in fund-allocation decision making problems in order to help make sound strategic infrastructure plans.

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