Dynamic Risk Assessment of Resilient Infrastructure Systems under Uncertain Conditions

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ABSTRACT: This paper proposes an adaptive risk management for civil infrastructure system in a dynamic stochastic environment, aimed at improving the ability of the system to adapt to changing conditions in the future. The proposed methodology is developed based on a rolling-horizon (RH) approach to (a) increase computational efficiency, (b) reduce uncertainties in the prediction of evolving conditions in the future, and (c) implement over an uncertain or infinite time horizon. The proposed RH-based adaptive risk management is applied to a decision problem where a hypothetical residential community in Kathmandu, Nepal is exposed to earthquake hazard as well as multiple evolving conditions. The results show that the proposed risk management significantly reduces the uncertainties in the prediction of the dynamic conditions and mitigates seismic risk to the community over time.

1. INTRODUCTION

In recent years, natural hazards with high consequences have made the public increasingly aware of the need for resilient civil infrastructure systems. Earthquakes, windstorms, floods, tsunamis, and wildfires can have adverse impacts on infrastructure systems while deterioration, service requirements, and constrained resources regularly challenge them over their life-cycle. The compounding effects of these disruptions have resulted in enormous human and economic losses, which naturally lead to an increasing attention from engineers, the insurance industry, regulatory authorities, and the public.

The challenges to civil infrastructure systems posed by such hazards have prompted numerous research programs that improve infrastructure resilience. Many of these studies (Tsonos, 2008; Deierlein et al., 2011) have focused on *the ability of systems to withstand disruptions* through risk mitigation measures, such as disaster-resistant design/retrofit/upgrade of structures, advanced design code and standards, etc. Some of the studies have investigated risk prevention and avoidance strategies (i.e., land-use planning or relocation in hazard-prone areas) (Burby et al., 2000; Glavovic et al., 2010) and risk transfer systems (i.e., catastrophe risk insurance) (Kunreuther, 2008; Field et al., 2012) to enhance *the ability of systems to prepare for disruptions*.

Various models also have been developed to simulate post-disaster recovery processes of infrastructure systems and communities (Miles and Chang, 2007; Lin and Wang, 2017; Burton et al., 2018) with the goal of enhancing *the ability of systems to recover rapidly from disruptions*. However, only a few studies have aimed at developing decision tools that support resilient infrastructure management focusing on *the ability of systems to adapt to changing conditions*.

Adaptive capacity is especially critical to civil infrastructure systems and communities which are subject to emerging conditions and dynamic changes in their operating and environmental demands. Current risk management strategies primarily focus on assessing life-cycle risks based on the assumption that information available at the beginning of the project is sufficient to provide reasonable estimates of future conditions over the entire decision horizon. Moreover, they assume strategies that appear optimal at the beginning are sufficient to ensure the functionality and resilience of infrastructure systems under future conditions. However, uncertainties arising from multiple evolving conditions may not be properly addressed by limited information and prediction models available at the time of decision-making. In addition, the presence of deep uncertainties arising from unexpected conditions, which probabilistic models are fundamentally unsuited to address, may lead to new problems of *ad hoc* revisions of strategies or time inconsistency in decision-making, which arise when the optimal strategy at present is no longer considered the optimal one in the future. Furthermore, current risk management usually identifies an optimal strategy for a pre-defined time horizon (i.e., the expected service life of infrastructure systems) while, in reality, the decision horizon is often uncertain (due to substantial uncertainties in evolving conditions and their effects on system performance) or even essentially infinite (for large-scale distributed infrastructure systems or communities).

This paper proposes an adaptive approach to risk management which addresses the above issues: reduction of uncertainties in the prediction of evolving conditions in the future and adaptive decisions over an uncertain or infinite time horizon. The proposed adaptive risk management is developed based on a rolling horizon (RH) approach which divides the entire decision problem into multiple sub-problems aimed at improving the reliability of prediction at every decision cycle and updating decisions based on better prediction. The remainder of the paper is organized as follows. Section 2 introduces the RH approach and describes the model of the proposed RH-based adaptive risk management. In Section 3, the proposed approach is applied to a hypothetical residential community in Kathmandu, Nepal under multiple sources of uncertainties. Section 4 summarizes the findings of the study.

2. ROLLING-HORIZON-BASED ADAPTIVE RISK MANAGEMENT

This paper proposes a RH-based adaptive risk management that improves *the ability of systems to adapt to changing conditions* by reducing uncertainties in the prediction of evolving conditions and updating decisions on a regular basis. This section begins with the introduction of a RH approach, followed by the description of the proposed risk management.

2.1. Rolling horizon approach

Generally, two decision approaches are available based on uncertainties in parameters that will affect decision variables described subsequently at the time of decision-making: a here-and-now decision approach and a wait-and-see decision approach. In the first approach, a decision is made before uncertain decision variables are observed, while the second approach allows decision-making after uncertain variables have been observed. A RH approach lies between these two decision approaches. Instead of making a decision considering all uncertainties which exist over the whole decision horizon, this approach divides the entire horizon into multiple reduced intervals and solves sub-problems sequentially by incorporating the realization of uncertain variables observed in the previous time step into decision-making for the next interval.

Decision-making for infrastructure systems often requires long-term prediction. As a projection horizon gets longer, however, prediction becomes less reliable and more expensive. Prediction becomes even more difficult if the infrastructure systems are subject to evolving conditions. Moreover, since the prediction of far-future events and conditions may have relatively small impacts on current decisions, one might adopt an approach in which forecasts are made for a finite period in the near future and the process is repeated sequentially for the entire decision horizon (Sethi and Sorger, 1991; Chand et al., 2002). This motivates a RH approach which decomposes the decision problem and solves multiple sub-problems sequentially by incorporating the realization of uncertain variables and the decisions made in the previous time periods (L_k). The sequential procedure of the RH approach is illustrated in Figure 1. At every time step (t_i), a fixed length projection horizon ($L_p = L_h + L_t$) is divided into head (L_h) and tail (L_t) parts. Reliable forecasts are available in the head part, which is also referred to as the roll period, while forecasts become less reliable in the tail part (L_t) as it extends to the medium-term time interval (Lu et al., 2016). The roll period (L_h) corresponds to the interval between successive decisions. The projection horizon (L_p) represents the forecast period that can lead to an optimal decision at the beginning of each time step. In other words, the projection horizon is sufficiently distant in the future so that the forecast beyond this horizon does not have significant effect on the optimal decision in the current time step. At every time step (t_i), the decisions made in the previous time steps (L_k) are known and fixed. The realization of uncertain variables in L_k is used to update the model which predicts the uncertain variables in the projection horizon (L_p) at t_i. Based on the prediction over L_p, the decision problem is solved for the entire projection horizon (L_p), but is implemented only for the roll period (L_h). At the next time step (t_{i+1}), a new projection horizon starts at the end of the roll period of the previous time step. The roll period keeps shifting forward (or “rolling over”) until the decision horizon ends (if the horizon is pre-defined) or the goals are met. In the latter case, the decision horizon is uncertain (or infinite) because it depends on uncertain infrastructure performance and a sequence of decisions that will be made in the future.

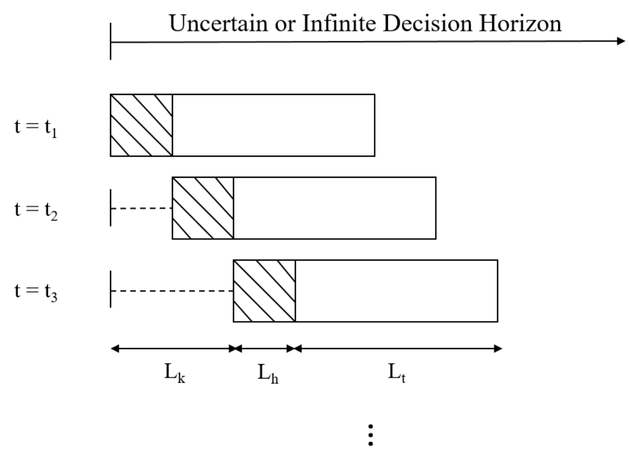

Figure 1: Sequential procedure of the RH approach (adapted from Lu et al., 2016).

RH approaches have been widely used to treat dynamic problems in inventory management, production planning, supply chain management, vehicle routing, demand-response control system among others. Chand et al. (2002) provided a comprehensive review on a RH approach primarily in operations management problems. Kostin et al. (2011) proposed a RH approach for strategic supply chain planning to reduce the computational burden and tested it for both finite and infinite horizon cases. Zamarripa et al. (2016) also utilized a RH approach for managing commodity supply chains, which required a large-scale mixed-integer linear programming model. By solving the smaller sub-problems, the RH framework greatly reduced the computational expenses while leading to sub-optimal decisions. Cordeau et al. (2015) proposed a RH algorithm in scheduling the daily deliveries of vehicles to dealers. Previous studies have shown that a RH approach is an efficient method for solving computationally expensive problems especially when subject to dynamic stochastic environments. However, only a limited number of studies have attempted to apply a RH approach to infrastructure resilience management problems. Section 2.2 will briefly introduce the need for a RH approach in the context of infrastructure resilience problems and describe a general procedure of the proposed adaptive risk management. The detailed structure of the proposed model will be introduced with an illustration in Section 3.

2.2. Modeling structure

Resilience management of large-scale infrastructure systems and communities requires a large set of random variables and involves high-dimensional computation. As described in Section 2.1, the computational efficiency achieved through the sequential procedure of the RH approach will be beneficial to infrastructure systems and communities that are situated in dynamic stochastic environments. It enables decision-makers to make a better prediction about highly uncertain future by sequentially incorporating data from previous time steps and adjust a series of decisions to improve their adaptive capacity to changing conditions. Moreover, the RH approach can be implemented over an uncertain finite or infinite time horizon.

In the RH approach illustrated in Figure 1, the adaptive risk management has three stages - prediction, decision, and monitoring - at every time step, t_i. The prediction stage provides forecasts about evolving conditions during the current projection horizon, which are used as inputs in decision stage. While the decision selected based on optimization is implemented for the roll period, evolving conditions are monitored and used to update the input data in the next time step (t_{i+1}) using dynamic Bayesian updating. The decision executed in the current time step is known at the beginning of the next time step and its effect on the system is also incorporated in the input data at the next time step. This procedure is illustrated in Figure 2. Each stage considers both system- or community-level and individual-level prediction, decision, and monitoring to consider their interactions in each stage. For example, in the case study which will be introduced in Section 3, the seismic risk management policy implemented affects individual homeowners' decision-making, while their decision-making may inversely affect the local government policy at the next time step.

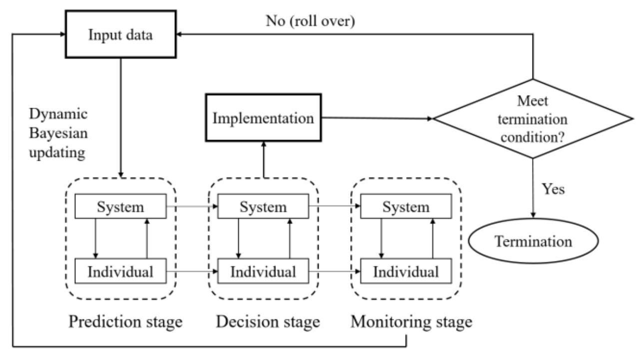

Figure 2: The structure of the proposed RH-based adaptive risk management.

3. CASE STUDY: A HYPOTHETICAL RESIDENTIAL COMMUNITY IN THE KATHMANDU VALLEY, NEPAL

The proposed RH-based adaptive risk assessment method is applied to a hypothetical residential community in the Kathmandu Valley, Nepal, which is a strong seismic-prone area, to show its advantage in managing seismic risks under multiple evolving conditions. In addition to earthquake hazards, the community is assumed to experience dynamic changes in exposure and vulnerability as a result of rapid population growth and urbanization (Lee et al., 2018). For example, existing residential buildings in the community expand vertically and/or horizontally in size as they are renovated to support population growth. Since such incremental building expansion is not guided by regulated building practices, the seismic vulnerability of a renovated building increases as it becomes larger (Lallemant et al., 2017). At the same time, the number of newly constructed buildings (i.e., community exposure to seismic risk) also increases due to population growth. A more detailed description of this community can be found in Lee et al. (2018).

3.1. Application of the proposed RH-based adaptive risk management

It is assumed in this case study that local government agencies and policy-makers make sequential decisions with the goal of minimizing seismic risks to buildings in the community. As identified in Lee et al. (2018), four seismic risk mitigation strategies are considered: (i) regulation to prohibit incremental expansion to the three most vulnerable building states (States 6, 7, and 9); (ii) regulation to prohibit incremental expansion to the five most vulnerable building states (states 5, 6, 7, 8, and 9); (iii) mandated seismic retrofit for the three most vulnerable building states; and (iv) mandated seismic retrofit for the five most vulnerable building states.

Theoretically, the decision timeframe in this study spans an infinite time horizon. Based on the RH approach, decisions are made sequentially at every 5 years (i.e., the 5-year roll period) with a 10-year projection horizon. At every decision point, the adaptive risk management has three stages as illustrated in Figure 3. In the *prediction stage*, population growth rates over the next 10 years are forecasted based on the existing prediction model available at the time of decision-making. These rates are subsequently used to determine the number of newly constructed buildings as well as the number of incrementally expanded buildings over L_p. At the same time, the seismic risk mitigation policy that will be taken during the current decision interval might affect the evolution of building state distributions during the following L_p. Based on the prediction of building state distributions, the expected earthquake-induced failure costs of the buildings that are accumulated over L_p can be computed. In the *decision stage*, the optimal policy that minimizes the expected cumulative failure costs of the community will be selected and implemented for the 5-year roll period. During this period, dynamic changes in population growth rates, which are the main drivers of increasing community exposure and vulnerability, are monitored and used to update the parameters of the existing prediction model in the next decision stage. Moreover, the updated building state distributions are also used to determine the optimal seismic risk mitigation policy for the next decision period. It should be noted that the policy implemented may affect individual homeowners' decisions about whether to: (a) expand and/or retrofit their existing building, or (b) construct new buildings (Lee et al., 2018). While it is important to incorporate such actions in the subsequent decision-making, they may be hard to quantify in a probabilistic manner due to the uncertainties arising from construction, retrofit, or labor-related costs, evolving risk attitudes, dynamic neighbors' communication, etc. Such uncertainties can be characterized by a scenario analysis within the RH-based adaptive risk management framework.

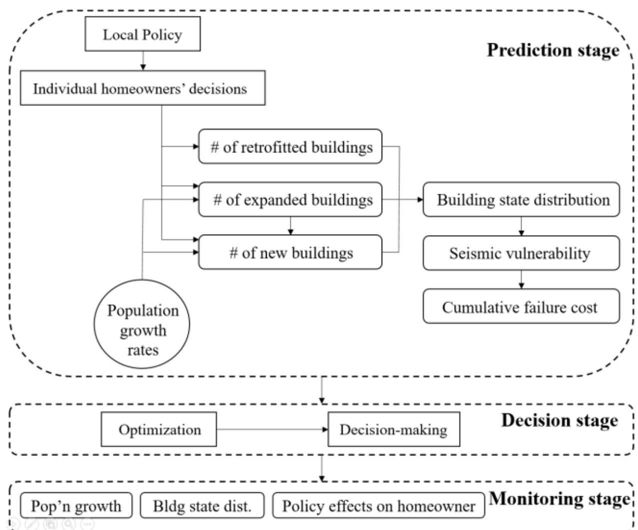

Figure 3: Three stages over the projection horizon

3.2. Results

The historical population growth rates in Kathmandu, Nepal (UN, 2014), which have been recorded at every 5 years since 1950, are used to construct the prediction models. The initial three data points (i.e., the growth rates recorded during the first 15 years) are used for the existing prediction model of the population growth rates available at the beginning (generally utilized in conventional decision-making) and the remaining data points are used to update the parameters of the sequential prediction models. More specifically, regression models are fitted to the data available at every decision point and their parameters, $\boldsymbol{\theta}$, and the error term, $\boldsymbol{\varepsilon}$, are modeled as random variables. Their distributions are sequentially updated through dynamic Bayesian updating when more data points become available at every time step.

Table 1: Comparison between the conventional and the proposed adaptive risk management: the MSE between the predicted and observed population growth rates; and the expected cumulative earthquake-induced failure costs of the buildings in the community ($E[C_f]$).

	MSE	*$E[C_f]$*
Conventional risk management	*0.0115*	*$ 1.811M*
Proposed adaptive risk management	*0.0090*	*$ 1.105M*

Table 1 illustrates the reduction of uncertainties in the prediction of population growth rates when using the proposed RH-based adaptive risk management. While the mean-square error (MSE) of the prediction model used in conventional risk management is 0.0115, the MSEs of the sequentially updated prediction models decrease over time and their mean value is 0.0090, which results in a 21% decrease in the MSE relative to the MSE of the existing prediction model fitted to the initial three data points. This leads to the reduction of uncertainties in the prediction of building state distribution evolution, and in turn, a reduction in seismic risk to the community, measured by the expected earthquake-induced failure costs of the buildings that are accumulated over a 50-year time period, $E[C_f]$, reported in Table 1. Based on more reliable prediction of population growth rates, building state distributions, and the associated failure costs of the buildings, the proposed adaptive risk management can better manage seismic risk to the community over time, leading to a 39% decrease in the expected cumulative earthquake-induced failure cost. Thus, the proposed risk management improves the ability of the community to respond to dynamic changes in the community exposure and vulnerability.

4. SUMMARY AND CONCLUSIONS

This paper introduces a RH-based adaptive risk management that improves *the ability of systems to adapt to changing conditions*. While various models (e.g., dynamic programming, heuristic simulation-based optimization, etc.) have been used to handle the dynamic nature of problems in infrastructure management, most of these models appear to be better suited for solving problems over a relatively short time horizon due to the exponential increase in problem size. The RH approach has a great potential to solve stochastic optimization problems over a long or even infinite horizon by reducing computational burden. In addition to its computational efficiency, the RH-based adaptive risk management can reduce the uncertainties in the prediction of evolving conditions and update decisions by incorporating new information on a regular basis. A case study involving a hypothetical residential community in Kathmandu, Nepal illustrates its advantages in managing seismic risk to the community under multiple evolving conditions. The results show that the MSE between the observed and predicted population growth rates is decreased by 21% as compared to the MSE of the prediction model used in the conventional risk management. Moreover, the proposed adaptive risk management results in a 39% decrease in the expected earthquake-induced failure costs of the buildings in the community by adjusting a series of decisions based on the better prediction.

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