Available online at www.sciencedirect.com

ScienceDirect

Procedia Engineering 212 (2018) 435–442

Procedia Engineering

www.elsevier.com/locate/procedia

7th International Conference on Building Resilience; Using scientific knowledge to inform policy and practice in disaster risk reduction, ICBR2017, 27 – 29 November 2017, Bangkok, Thailand

Adaptive Decision Framework for Civil Infrastructure exposed to Evolving Risks

Ji Yun Lee[a,]*, Henry Burton[b], David Lallemant[c]

[a]*Washington State University, Department of Civil and Environmental Engineering, Pullman, WA 99164, USA*
[b]*University of California, Los Angeles, Department of Civil and Environmental Engineering, Los Angeles, CA 90095, USA*
[c]*Nanyang Technological University, Asian School of the Environment, Singapore*

Abstract

Adaptive decision-making (ADM) is a structured process of learning, improving understanding, and ultimately adapting management decisions in a systematic and efficient way, aimed at reducing uncertainties over the course of the management timeframe. This approach holds a great potential for dealing with the challenges faced by civil infrastructure facilities, especially those exposed to evolving risks caused by changes in environmental and urban settings, evolving expectations and preferences of the public, tightening budgets, and unpredictable political circumstances over their lifetime. This paper suggests ADM as a way of continuously reevaluating the risks and providing more adaptive and flexible management actions to enhance infrastructure resilience under dynamic changes and evolving conditions. The proposed ADM is illustrated with a benchmark problem based on a testbed residential community in Kathmandu, Nepal to explore the effect of incremental building expansion on the seismic risk to a community and examine the feasibility and effectiveness of ADM in improving resilience.

Peer-review under responsibility of the scientific committee of the 7th International Conference on Building Resilience.

Keywords: Resilience; Decision-making; Adaptive management; Earthquake Engineering; Risk assessment; Building expansion; Structural Engineering

1. Introduction

Decisions aimed at ensuring the adequate performance and operational integrity of civil infrastructure exposed to

* Corresponding author. Tel.: +1-509-335-3018; fax: +1-509-335-7632.
E-mail address: jiyun.lee@wsu.edu

1877-7058 © 2018 The Authors. Published by Elsevier Ltd.
Peer-review under responsibility of the scientific committee of the 7th International Conference on Building Resilience
10.1016/j.proeng.2018.01.056

natural hazards have strong implications to the health and financial well-being of the communities that they serve. Quantitative risk-informed decision methods are required to assess the effectiveness of engineering strategies – design, maintenance and rehabilitation – in mitigating the risk to civil infrastructure over their service periods (through risk assessment) and to establish investment priorities within financial constraints (through optimization techniques). Although current probabilistic risk assessments have enabled informed management and decision-making of civil infrastructure, in many cases, such analyses are static, focusing more on understanding current risks. Disaster risks to civil infrastructure, however, have been increasing rapidly due to continually changing urban environments, increasing operational and social demands, technology development, and global climate change. For example, incremental building expansion in many developing countries plays a significant role in increasing their seismic collapse vulnerability [1]. Also, in recent years, there has been growing evidence that global climate change may result in more frequent and increasingly severe extreme natural hazard events, such as hurricanes, tsunami, floods, droughts, etc., which trigger more damage to civil infrastructure and the associated economic and human losses [2]. In this context, disaster risks to civil infrastructure are not static, and continuous reevaluation over time is required to move towards a more resilient future.

Resilient development has become a new standard for civil infrastructure design and maintenance, as well as community development. Its interpretation may vary depending on its application, but seismic resilience of system/community often is thought of as including three measures: reduced failure probabilities, reduced consequences from failures, and reduced time to recovery [3]. This paper places emphasis on the first two measures of resilience, which relate to pre-disaster mitigation, by enabling decision-making process to incorporate the effects of dynamic conditions and evolving risks in life-cycle performance assessment and to become more adaptable to those changes and surprises. Due to our incomplete knowledge of dynamic conditions in hazard, exposure and vulnerability (and the associated uncertainties), unintended consequences may occur and challenge the resilience of civil infrastructure systems and the community functions that they support. Adaptive decision-making (ADM) arises out of the need for flexible and responsive approaches to managing the risk to civil infrastructure exposed to changing environments. Such decision methods will be able to respond successfully to evolving risks and future changes and to achieve their short/medium-term and long-term resilience objectives.

To begin with, this paper briefly introduces an adaptive decision method as a way of continuously reevaluating the risks and, where necessary, updating decisions over time. The proposed ADM is demonstrated based on a changing urban environmental condition, where incremental building expansion and population growth occur simultaneously, to show its feasibility in reducing seismic collapse vulnerability of buildings and eventually improving the resilience of a community.

2. Adaptive decision-making and its application: a residential community of Kathmandu Valley, Nepal exposed to evolving risks due to increased exposure and vulnerability due to growing populations

2.1. Adaptive decision-making

Decision-makers are challenged by inherent uncertainties and an incomplete knowledge base, especially when making decisions involving changing conditions. Surprises and changes lead decision-makers to adjust plans and strategies as new information accumulates over time and to incorporate improved understanding in risk-informed decision-making. Adaptive management is a structured process to make this learning in a systematic and efficient way, aimed at reducing uncertainties. The goal of adaptive management is to improve decision-making through learning processes. It provides flexible and responsive management protocol, which evolves over time through an iterative process of planning, monitoring, and adjusting strategy (as shown in Fig. 1): goals and objectives are set; the management action is implemented; the effects of the action are monitored and evaluated to collect new information; and the action is adjusted based on monitoring results [4]. Through this process, adaptive management explicitly recognizes evolving conditions and reduces the uncertainties by incorporating lessons learned into future decisions through explicit mechanisms for linking new information from monitoring to the decision.

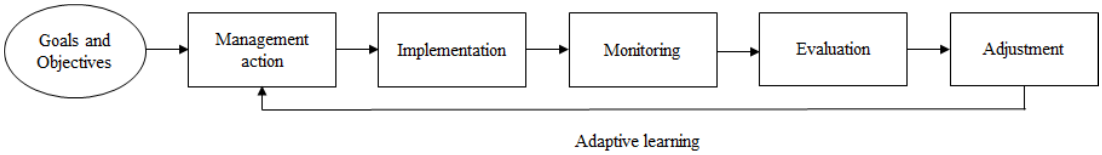

Fig. 1. Adaptive management process.

2.2. Problem statement

In many developing countries, households start with simple one or two-story shelters and expand over time vertically (with additional stories) and/or horizontally (with additional cantilevers above sidewalks or streets) due to population growth, family expansion and urbanization. Incremental building expansion is informal and not based on either regulated building practices or planned development. Such expansion increases the seismic vulnerability of buildings, and eventually affects the resilience of the community that they support [1]. In addition to building expansion, a community also expands over time by adding more houses and supporting facilities, given population increase in that community. In the benchmark problem, a hypothetical residential community in the Kathmandu Valley, Nepal is considered to illustrate the application of adaptive management to decision problem in dealing with evolving risks over time.

A hypothetical residential community is assumed to be located on the outskirts of Kathmandu City and consists of 100 buildings at the present time ($t = 0$). It is assumed that all the buildings in a community are relatively close together and experience the same level of ground motion for a given earthquake scenario. Under this assumption, a site-specific seismic hazard curve for this community has been developed based on ten independent seismic sources. A detailed description of a probabilistic seismic hazard analysis for Kathmandu City, Nepal can be found in [5].

It is assumed that 75% of the existing buildings in the hypothetical community are one-story buildings (State 1 in Fig. 2) and the rest are two-story buildings (State 2 in Fig. 2). The buildings expand incrementally, while new buildings are constructed every year. Again, 75% of the newly constructed buildings are initially in State 1, 25% are in State 2, and then they evolve over time. Fig. 2 presents nine states of residential buildings constructed with reinforced concrete frames with masonry infill, as developed by [1] to simulate building expansion sequences and assess changing seismic risk over time. Building states distribution over time is modeled as a discrete-time Markov chain with a transition probability matrix describing the probabilities of particular transitions from one state to another. Collapse fragility curves for the nine building states are assumed to follow lognormal cumulative distribution functions with the median values and logarithmic standard deviations shown in Table 1.

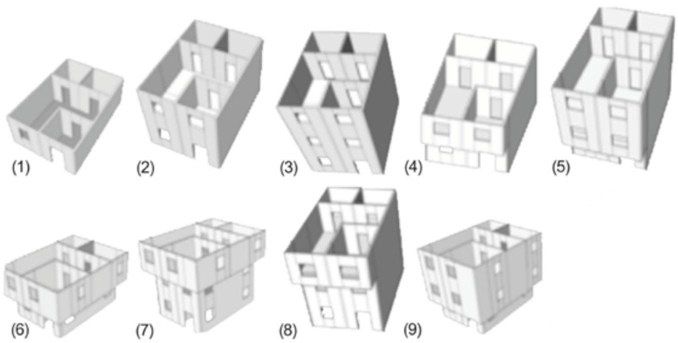

Fig. 2. Nine states of typical residential buildings in Kathmandu, Nepal.

Table 1. Median values (normalized by the gravitational constant) and logarithmic standard deviations of collapse fragility curves for all building states.

	State 1	State 2	State 3	State 4	State 5	State 6	State 7	State 8	State 9
Median	1.93	0.85	0.56	0.69	0.51	0.38	0.37	0.51	0.37
log σ	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5

2.3. Sequential decision tree

Local government agencies or policy makers are examples of entities who are responsible for making decisions to manage the seismic risks to buildings in a community and their decisions should be based on quantitative evidence and a systematic approach that reflects both aleatory and epistemic uncertainties embedded in life-cycle performance of buildings as well as the conditions to which they are subjected. In this study, the decision model evaluates four alternative actions designed to reduce the seismic risk to the community in addition to status quo: (i) no action; (ii) regulation to limit the most three vulnerable building states (States 6, 7, and 9); (iii) regulation to limit the most five vulnerable building states (States 5, 6, 7, 8, and 9); (iv) seismic retrofit to the most three vulnerable building states; and (v) seismic retrofit to the most five vulnerable building states. In alternatives 2 and 3, additional new buildings are constructed every year to offset the number of unoccupied people due to the limited states of buildings. Seismic retrofit in alternatives 4 and 5 is assumed to result in 50% increase in the median values of the collapse fragility curves relative to the unretrofitted buildings.

Different population growth rate scenarios are considered to be external factors affecting incremental building expansion as well as the number of new buildings constructed annually. For simplicity, three population growth rate scenarios are considered in this decision problem: slow, moderate, and fast population growth rates are estimated from the latest revision in [6]. Rates for each scenario and the associated probabilities are summarized in Table 2. The transition probability matrix of the Markov chain, which is used to model incremental building expansion, is different for each population growth rate scenario: the same transition probability matrix used in [1] is utilized for the moderate scenario, while some of the elements in the matrices are adjusted for slow and fast scenarios to retard or expedite building expansion progress.

Table 2. Population growth rate scenarios and the assigned probabilities.

	Slow	Moderate	Fast
Annual growth rate	1%	3.5%	6%
Probability	0.2	0.6	0.2

In this study, five decision points are considered over a 50-year time horizon, at every 10-year interval from the beginning of the considered duration. Decisions can be changed adaptively at each decision point or kept the same over time. Population growth rate scenarios are also altered at each decision point, but assumed to be stationary during the interval (between t_i and t_{i+10}, in this case). This decision model can be represented graphically by the decision tree as shown in Fig. 3. At the beginning of the period, five alternative actions are evaluated using the information about the state of nature (summarized in Table 2) available at t_1 and the initial decision is made based on the criterion. Once the time approaches the second decision point t_{11}, the true state of nature θ_1 (population growth rate during the first interval) would be known. As a result of having taken decision 1 and having found the true state θ_1, the building state distribution at t_{10} and the total cost of a community accumulated over the first phase can be calculated. At decision point 2, t_{11}, a decision-maker may or may not have new information about the state of nature. With the current knowledge on population growth rate scenarios, any of the five alternatives can be selected based on the same or different criteria for the next 10 years. This case study simulates a five-period decision process (period one; period two; and so forth), in which the same decision-making processes described above are repeated five times over 50 years. Five alternatives and three population growth rate scenarios in one period result in 15 possible combinations and yields 759,375 outcomes over the entire time period considered. The combination of five decisions in five periods determines the cumulative life-cycle cost of the hypothetical residential community. The process to obtain the total life-cycle cost (LCC) of each output will be introduced in the next subsection.

2.4. Total life-cycle cost of a residential community

In this benchmark problem, the alternatives are evaluated based on life-cycle cost (LCC) and the alternative with the minimum LCC is selected as the optimal strategy at each decision point. In this study, the total expected life-cycle cost of a small residential community of interest, t, is:

$$E[C_L] = E[C_C] + E[C_D] + E[C_E] + E[C_R] \tag{1}$$

where $E[C_C]$ is the expected cumulative construction cost, $E[C_D]$ is the expected cumulative damage cost, $E[C_E]$ is the expected cumulative building expansion cost, and $E[C_R]$ is the expected cumulative seismic retrofit cost. Each term will be introduced in more details in the next subsections.

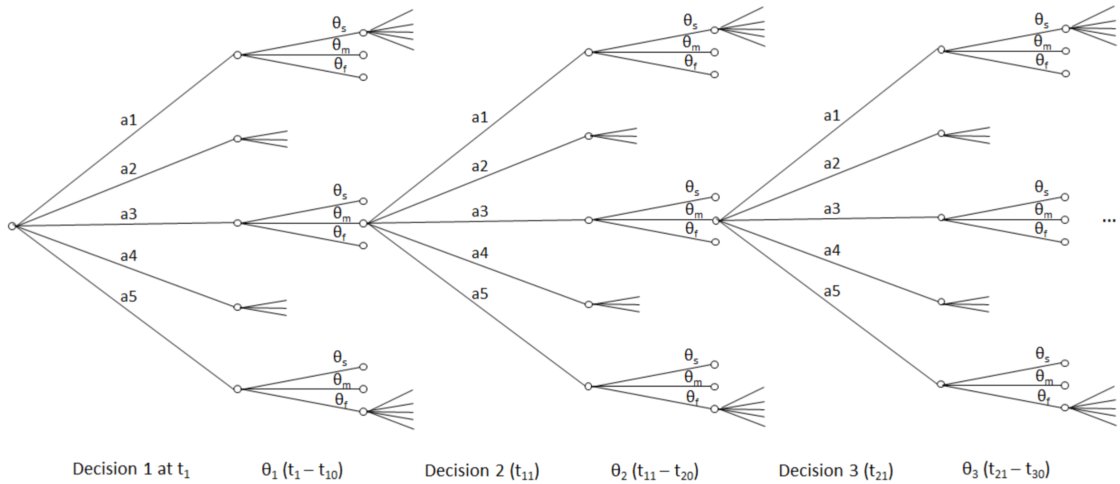

Fig. 3. Partial decision tree for sequential decisions over 50-year time period.

2.4.1. Cumulative construction cost, $E[C_C]$

As discussed previously, the community of interest expands over time due to incremental building expansion and new construction. The number of new buildings constructed each year (t_i) is calculated from the gap between the population expected at year (t_i) and the number of people living in the existing buildings. Construction costs are assumed to be \$48,000 and \$66,000 for States 1 and 2, respectively. The costs are calculated from the combination of \$50 per square foot for land and \$30 per square foot for construction materials and labor.

The baseline building has 3 bays in the long direction and 2 bays in the short direction and each bay spans 10 ft. Therefore, the area of each floor is 600 ft^2. The cantilevers in any direction of the building extensions are all equal to 5ft. In this way, the areas of all building states in Fig. 2 can be calculated. The square footage of living space per person in Kathmandu, which is used to determine the number of people in a given building, is assumed to be 200 square feet.

The expected cumulative construction cost, $E[C_C]$, becomes:

$$E[C_C] = E\left[\sum_{i=1}^{t\_life}\sum_{j=1}^{2}\frac{N_c(t_i, j)C_c(j)}{(1+r)^{t_i}}\right] \tag{2}$$

where $N_c(t_i,j)$ is the number of newly constructed buildings in State j (recall that newly constructed buildings are either in State 1 or 2) at time t_i, $C_c(j)$ is the construction cost of building state j, and r is a discount rate.

2.4.2. Cumulative damage cost, $E[C_D]$

In this problem, collapse is the only limit state considered. The seismic hazard is introduced in Section 2.2 and material aging and structural deterioration process are not considered in this study. In other words, the only factor affecting the seismic vulnerability of buildings is incremental building expansion. The expected cumulative damage cost over the lifetime is:

$$E[C_D] = E\left[\sum_{i=1}^{N(t)}\sum_{j=1}^{n\_type}\frac{N_f(t_i, j)C_f(j)P_i(j)}{(1+r)^{t_i}}\right] \tag{3}$$

where *N(t)* is the total number of seismic hazard events over the life-cycle, n_type is the number of building states, $N_f(t_i,j)$ is the number of buildings in State *j*, $C_f(j)$ is the failure cost of building state *j*, and $P_i(j)$ is the probability of failure of building state *j* given the i^{th} occurrence of one or multiple seismic hazard events.

The failure cost of building state *j*, $C_f(j)$, includes damage (reconstruction) cost, loss of contents, demolition cost, debris cost, temporary shelter cost, human loss, and injuries. A collapsed building is assumed to be reconstructed with seismic strengthening for greater structural robustness immediately after collapse. Consequently, the damage costs of one, two, and three-story buildings are assumed to be \$50,400, \$69,300 and \$88,200 respectively with the additional 5% taken to be the cost of enhanced seismic robustness. Content losses and the cost of temporary shelter are taken to be \$17/ft^2 [7] and \$100/person respectively (time factor is not considered here). The same costs for demolition (\$3,000) and debris clearance (\$2,500) are applied to all building states [8]. Total injury costs are calculated from floor area multiplied by expected injury rates (40% minor injuries and 40% serious injuries), occupancy rate and injury costs. Minor injury cost is \$1,000/person and serious injury cost is \$10,000/person [7]. Assigning an economic value to human life has been controversial, but in this study, \$6.3M is allocated to the value of a human life in accordance with the most recent recommendations of the Federal Emergency Management Agency. The expected human loss rate is 20% of occupancy rate.

2.4.3. Cumulative building expansion cost, $E[C_E]$

Incremental building expansion each year is modeled as a discrete-time Markov chain, as discussed in Section 2.2. The expected cumulative building expansion cost is:

$$E[C_E] = E\left[\sum_{i=1}^{t\_life}\sum_{m=1}^{n\_type}\sum_{n=1}^{n\_type}\frac{N_{mn}(t_i)C_{mn}}{(1+r)^{t_i}}\right] \tag{4}$$

where $N_{mn}(t_i)$ is the number of buildings changing from State *m* to State *n* at time t_i, and C_{mn} is the expansion cost from State *m* to State *n*. C_{mn} is evaluated as a function of floor area, and its unit cost is \$30/ft^2.

2.4.4. Cumulative seismic retrofit cost, $E[C_R]$

This term is applied only when alternative 4 or 5 is selected in the decision phase. The expected cumulative seismic retrofit cost is:

$$E[C_R] = E\left[\sum_{i=1}^{t\_life}\sum_{j=1}^{n\_type}\frac{N_R(t_i, j)C_R(j)}{(1+r)^{t_i}}\right] \tag{5}$$

where $N_R(t_i, j)$ is the number of buildings in State *j* retrofitted at time t_i and $C_R(j)$ is the retrofit cost of a building in State *j*. Retrofit cost is assumed to be 5 percent of the total construction cost.

Note that the annual discount rate used here is assumed to be constant at 3.5% while time-declining discount rate is preferred for longer time horizon [2].

2.5. Results

Customary minimum life-cycle cost analysis selects an action among available alternatives that minimizes the expected cumulative cost over the considered duration. A decision is made at the beginning of the time-horizon and is not expected to change. For this reason, the rate of future population growth in the next 50 years, which is uncertain at the time of decision being made, should be estimated in a probabilistic manner. Total life-cycle costs resulting from the initial decision and the performance of buildings in the community under different population growth rate scenarios are presented in Table 3. If true state of nature for the next 50 years is slow population growth, alternative 3 would result in the lowest total expected life-cycle cost of the community. This is mainly because only a small number of buildings need to be constructed under the slow scenario and alternative 3, which is largely governed by construction cost, becomes the best strategy. Alternative 5 is the optimal choice for the moderate population growth scenario because this strategy encourages building expansion by lowering construction cost, while strengthening incrementally expanded buildings at a relatively low cost (5% of construction cost). However, under the fast scenario, the difference between total LCC resulting from alternatives 2 to 5 is not significant. In this case, it is hard to find the absolutely best decision, especially when considering substantial uncertainties embedded in population growth rates and the associated building state distribution under the fast scenario. As shown in the Table 3, the optimal strategies are sensitive to future population growth rate scenarios and non-adaptive decision-making based on current knowledge would be unwise given the probable future scenarios for a period of 50 years.

Table 3. Total expected life-cycle cost for each alternative under different population growth rate scenarios: no decision alteration.

	Slow growth	Moderate growth	Fast growth
Alternative 1	8.87	14.54	34.01
Alternative 2	7.38	13.17	30.93
Alternative 3	6.88	13.11	30.65
Alternative 4	7.78	13.13	30.61
Alternative 5	7.54	12.93	30.13

Unit: US Million dollars

Table 4 shows the overall outcomes of each alternative, considering all possible population growth rate scenarios and the associated probabilities over the entire time period. As described previously, conventional decision-making chooses the initial action at t_1, which remains unchanged over time. Alternative 5 results in the lowest total expected life-cycle cost. The best overall strategy for the entire time period, considering all possible population scenarios, is therefore the seismic retrofit policy for the most five vulnerable building states (States 5, 6, 7, 8, and 9).

Table 4. Total expected life-cycle cost under all possible population growth rate scenarios.

	Alternative 1	Alternative 2	Alternative 3	Alternative 4	Alternative 5
Total cost	75,870,706	68,484,092	67,711,976	68,235,142	66,914,337

Unit: US dollars

To reduce the uncertainties associated with future building state distributions and the associated costs, multiple variables may need to be monitored to characterize the relevant dynamics of the urban environment. For the purpose of simplification, however, population growth rate over time is the only variable monitored in this study. Monitoring does not always provide perfect information about the states of nature, because the observed state is not a perfectly reliable estimate of the true state because of measuring errors, etc. Table 5 shows the assigned conditional probabilities associated with the monitoring plan used in this study.

Table 5. Monitoring quality and the associated probabilities.

Actual state	Observed state	Probability
θ_1	z_1	0.90
θ_1	z_2	0.05
θ_1	z_3	0.05
θ_2	z_1	0.05
θ_2	z_2	0.90
θ_2	z_3	0.05
θ_3	z_1	0.05
θ_3	z_2	0.05
θ_3	z_3	0.90

In ADM, the decision-maker can alter actions adaptively over time. To evaluate the ability to switch the alternatives in the subsequent periods, suppose that the population will evolve over time: the sequence of true states is (θ_1 = slow, θ_2 = slow, θ_3 = moderate, θ_4 = moderate, and θ_5 = fast). However, at time t_1, the decision-maker does not know which state of nature θ_1 is the true one and should make a decision using current knowledge (Table 2). All alternatives are evaluated based on expected cumulative life-cycle cost over the next 10 years and alternative 2 is selected as the initial decision. During the ten years following the initial decision, population growth rate is monitored and the first monitoring result (z_1) is assumed to be slow. This result is used to update the probability distribution of states in making the second decision at t_{11}. If another 10 years of monitoring following the second decision results in z_2 = slow, the posterior probability of the first monitoring becomes the prior probability in the second monitoring. Moreover, if the rest of monitoring results are (z_3 = moderate, z_4 = moderate, and z_5 = fast), the best strategy becomes the sequence of ($a_1 = 2$, $a_2 = 3$, $a_3 = 3$, $a_4 = 5$, $a_5 = 5$). The seismic collapse rate of a community is calculated as the ratio of the number of collapsed buildings over the service period to the total number of buildings. Conventional minimum life-cycle cost analysis results in a 0.0093 of seismic collapse rate while only 0.006 of collapse rate is expected when using ADM. Such evolving decisions bring in 35% decrease in seismic collapse rate and 14% decrease in total life-cycle cost, leading to the conclusion that the ability to change actions based on updated knowledge would reduce seismic risks and the associated costs and improve risk-informed decisions over time.

3. Conclusion

This paper has addressed evolving conditions in which civil infrastructure systems are situated and suggested the transition from current practices to an ADM, aimed at continually improving decisions by learning from the results of monitoring or experiments and thereby reducing their vulnerability to evolving risks. As shown in the benchmark problem, ADM allows flexible decision-making processes that can be modified as new information and understanding become available and improves the ability to deal with future changes and surprises so that the community can be dependably managed in the future. Through ADM, seismic risks (in terms of both the seismic collapse rate and total expected cost) to the community can be reduced to better ensure its seismic resilience.

In this paper, resilience is not explicitly measured quantitatively, but is achieved by improving the ability of civil infrastructure to withstand future changes and surprises and successfully adapt and respond to those evolving risks. ADM has a great potential in reducing vulnerability and increasing resilience to improve the well-being of a community/society, especially when perfect knowledge about a system and the state of nature is not available at the present time and risks evolve over time. Decisions obtained from ADM not only enable systems to become more resilient to changing conditions but also contribute to the resilience of future generations. Moreover, although ADM has been demonstrated in this paper based on a changing urban environment condition (where incremental building expansion and population growth occur simultaneously), it has a wide range of applicability, such as shifts in social and political needs and preferences, technological progress, global climate change, evolving urban settings, changing budget cuts, etc. Coupled with the natural and social sciences, ADM may also increase ecological and social resilience and hence increase the ability to respond to evolving risks in the future.

References

[1] D. Lallemant, H.V. Burton, L. Ceferino, Z. Bullock, A. Kiremidjin, A framework and case study for earthquake vulnerability assessment of incrementally expanding buildings, Earthquake Spectra, 2017.
[2] J.Y. Lee, B.R. Ellingwood, A decision model for intergenerational life-cycle risk assessment of civil infrastructure exposed to hurricanes under climate change, Reliability Engineering & System Safety, 159 (2017) 100-107.
[3] M. Bruneau, S.E. Chang, R.T. Eguchi, G.C. Lee, T.D. O'Rourke, A.M. Reinhorn, M. Shinozuka, K. Tierney, W.A. Wallace, D. von Winterfeldt, A framework to quantitatively assess and enhance the seismic resilience of communities, Earthquake Spectra, 19 (2003) 733-752.
[4] G. Lessard, An adaptive approach to planning and decision-making, Landscape and Urban Planning, 41 (1998) 81-87.
[5] S. Shrestha, Probabilistic seismic hazard analysis of Kathmandu city, Nepal, International J. Engineering Research and General Science 2 (2014).
[6] United Nations, World urbanization prospects, the 2014 revision, United Nations, 2014.
[7] Y.K. Wen, Y.J. Kang, Minimum building life-cycle cost design criteria. I: methodology, J. Structural Engineering, 127 (2001) 330-337.
[8] National Planning Commission, Nepal earthquake 2015: Post disaster needs assessment. Vol. B: Sector Reports. Kathmandu, Nepal, 2015.