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Multicriteria decision making for selecting an optimal survey approach for large building portfolios

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ABSTRACT

Technological advances and innovations have led to various pre- and post-disaster data collection alternatives. Hence, selecting a suitable survey approach may be challenging for different decision-makers. This paper proposes a multicriteria decision-making (MCDM) method to choose the optimal survey approach to gather exposure information needed for reliable multi-hazard risk assessment of large building and infrastructure portfolios. Both deterministic and stochastic implementations of MCDM are investigated, considering primary sources of aleatory and epistemic uncertainties. The applicability of the proposed framework is demonstrated for a portfolio of 13,200 buildings in a hypothetical multi-hazard prone region. The results show that informed decisions on identifying an optimal survey technique could be efficiently derived using MCDM and a number of relevant criteria. The proposed methodology can support various decision-makers in pre- and post-disaster risk modeling and management/reduction.

1. Introduction

Risk-informed decisions are essential for devising suitable and effective disaster mitigation, preparedness, response, and recovery strategies. Such decisions rely on the availability of data to model and quantify the hazards of concern (and their potential interactions) as well as the exposure, physical and social vulnerabilities of assets/infrastructure and people/networks in a given region. An essential step in evaluating single and multi-hazard risks from natural hazards such as earthquakes (and their cascading hazards – e.g., tsunamis, landslides, liquefaction), floods, and storms is the development of a reliable inventory of assets at risk (e.g., buildings, infrastructure components) in the region of interest.

Developing adequate and accurate building inventories in a hazard-prone region enables risk modelers to perform more accurate simulations to identify/prioritize vulnerable structures/infrastructure systems. Similarly, these types of inventories can support practicing engineers to develop performance-based assessment and retrofit procedures for archetypal collapse-prone buildings that can be implemented efficiently on a community/regional scale. Furthermore, building asset owners and other stakeholders (e.g., (re-) insurance firms and business investors) can more precisely evaluate their risk profiles within a regional building stock. Finally, local authorities can make more risk-informed decisions on resilience-enhancing strategies for their vulnerable assets and resource-constrained investments.

The data collection process for building inventory development generally focuses on the information required to assess the building stock's physical vulnerabilities. For instance, data collection forms in existing guidelines and scientific literature (e.g., Refs. [1,2]) can be adopted to rapidly collect data and screen buildings for potential single and multi-hazard scenarios. Traditional data collection

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procedures involve a paper-based sidewalk visual survey of each building in the considered portfolio or a sample of them. A sidewalk visual survey has its challenges – the vast human, time, and financial resources needed to be deployed, particularly for large building portfolios. The time resources include person-days of preparation time, travel time to/between surveyed buildings and inspection time of each building, digitization of data (in the case of paper-based surveys), etc. Also, the number of surveyors required for an extensive building portfolio increases human error, especially when some subjective judgments are needed. The financial aspect could also be a significant hurdle. For example, a proposed Utah school building inventory of about 900 schools for seismic vulnerability assessment purposes would have cost $500,000 at an anticipated cost of $300 - $600 (including travel costs) per building [3]. Also, sidewalk surveying has become even more challenging in recent times, given health concerns related to the COVID-19 pandemic and the dwindling financial power of governments in the developing and developed world. Hence, it is crucial to investigate and potentially adopt efficient and effective options for surveying large building portfolios.

Recent technological progress and innovations have led to the development of various data collection alternatives to the traditional sidewalks using remote sensing, global positioning systems (GPS), digital video/photography, unmanned aerial vehicle (UAV) systems, and geographic information systems (GIS) [4–6]. These advanced techniques are developed to address the challenges mentioned above of traditional sidewalk surveying. However, despite the enormous advantages of these approaches, their applicability depends on the aim and scope of the building inventory development, size of the building portfolio, available budget, and technical know-how of potential users, among other factors.

Given the pros and cons of the available data collection procedures, local authorities and other end users may face the challenge of selecting a suitable approach (or a combination of approaches) that satisfies the aim and objectives of their building inventory development and analysis. To choose an optimal survey approach for their building portfolios, decision-makers must consider various conflicting criteria (e.g., economic and human factors/costs, time, and accuracy). There are, however, currently no frameworks for selecting a suitable alternative from a subset of candidate survey approaches.

Selecting a suitable survey approach requires developing a multicriteria decision-making (MCDM) framework. MCDM is widely accepted as a reliable procedure that can incorporate multiple and conflicting criteria as well as end-user preferences into a rational decision process for different applications [7–9]; moreover, it can include both qualitative and quantitative criteria/indicators. The outcome of MCDM is the selection of a best-fit survey approach from a subset of candidate alternatives given various levels of uncertainties.

This study specifically describes a multicriteria decision-making method for selecting a suitable survey approach from a subset of candidate survey approaches, considering economic, human-time, and health and safety factors. Furthermore, a probabilistic procedure is presented to deal with various sources of aleatory and epistemic uncertainties in the decision-making process. The proposed approach is demonstrated using a portfolio of buildings in a hypothetical region susceptible to multiple hazards. Various stakeholders can adopt the proposed approach for selecting optimal survey techniques for pre- and post-disaster risk assessment and management purposes.

2. Data collection methods for disaster risk assessment

The data collection process for developing a building inventory typically involves data from various sources. For example, census data may be available on building use and occupancy, including some limited structural information. Also, hazard characteristics at a given site/for a given region are typically available in hazard maps from the existing literature or official national geological surveys in a given country. However, structural modifications or information on specific structural attributes, which are fundamental predictors of a building performance, may be unavailable due to lack/loss of documentation. As earlier mentioned, such data can be collected using a traditional sidewalk visual survey. This section, however, focuses on describing alternative techniques to such an approach.

To explore a cost-effective alternative to sidewalk surveying for data collection using 'off-the-shelf' techniques and equipment, Montoya [5] proposed a dual-stage methodology that combines remote sensing, GPS, digital video, and GIS. The first stage of the Montoya methodology involves using remote sensing (aerial images) and GIS tools for stratification and planning purposes. The stratification process entails using aerial photos to assess the homogeneity of the building stock in the considered region. The aim is to identify the feasibility of reduction in the data collection phase (i.e., in homogeneously-built areas such as housing estates). GIS tools are then used to determine the optimal travel route for a moving vehicle to capture the digital video in a second stage. Such a second stage involves using a combination of GPS and digital video to produce images of building facades along the identified driving route. The collected images are then manually interpreted to extract the relevant attributes for building inventory development purposes.

Ploeger et al. [6] developed an integrated dual-component GIS-Google-Android system, called the Urban Rapid Assessment Tool (RAT), as an alternative to sidewalk surveying. The first component of the Urban RAT system is the Urban RAT Desktop, a combination of street-view, aerial imagery, and base map layers within an ArcGIS system and a digital data entry form for documenting the attributes of the assessed building. The second component of the system is the Urban RAT Mobile which serves as an electronic platform for collating data during warranted sidewalk surveys (i.e., in cases where the Urban RAT Desktop is deemed insufficient for data collection purposes). By testing the tool out in a case-study area, the authors highlighted that for the same inventory, the sidewalk survey required more than four times the time expended through the Urban RAT Desktop. Furthermore, based on correlation analysis on collated data on buildings surveyed through the sidewalk and remote surveys, the authors concluded that the Urban RAT tool is a viable proxy for the traditional sidewalk-based procedure.

To address the cost and complexity of existing approaches and tools, Opabola et al. [10] proposed a mixed-mode strategy for surveying large building portfolios using a combination of sidewalk and remote survey approaches. The remote survey entails using open-source GIS information with open-source street-view and satellite-view images. In the Opabola et al. study, a small proportion (dependent on the homogeneity of the building portfolio) of the building portfolio is surveyed using both sidewalk and remote survey approaches. First, the homogeneity of the building portfolio is assessed in terms of building age, the number of stories, type of lateral load-resisting system (if known), and building occupancy type (i.e., residential, office, or industrial). Subsequently, an inter-rater reliability analysis (to evaluate the intraclass correlation coefficient ICC) on the data collected from both the sidewalk and remote surveys is used to assess the deployability of the remote survey to the remaining building portfolio. The remote survey is employed for building classes with ICC values above a specified minimum ICC. In cases where the minimum criterion is not satisfied, a sidewalk survey is recommended. The approach was demonstrated in collecting building inventory data of over 2,500 school buildings in the Central Sulawesi region of Indonesia. Furthermore, the authors highlighted the improved cost-benefit of the remote survey technique. Apart from the lower person-time and cost for carrying out the remote survey relative to the sidewalk survey, fewer surveyors are needed, ensuring that the influence of person-to-person subjectivity/variability (and related errors) on the collected data is significantly reduced.

Studies [4,11–13] have proposed using unmanned ground (UGV) and aerial vehicle (UAV)-based photogrammetry and geo-computing for data collection for pre-disaster risk assessment and post-disaster damage estimation of buildings and critical infrastructure. Apart from the images collected for data collection, these studies have used Structure from Motion (SfM) algorithms to develop 3D models of surveyed structures for various disaster risk management purposes. It is also noteworthy that UAV technology can also be adopted to monitor topography, floodplain evolution, and the presence of volcanoes (and their characteristics). Given the level of accuracy of UAV photogrammetry in developing 3D models of buildings and its broad availability, it is considered a good alternative for data collection.

Similar to the UAV-based photogrammetry approach for data collection, studies [14–16] have adopted information from terrestrial laser scanners (TLSs), carrying out 3D structure surveys and developing 3D models of assessed damaged and undamaged structures. In addition, recent studies [16,17] have further demonstrated the applicability of laser scanning data in developing finite element models for structural analyses purposes, even for structures with complicated arch geometries.

As described above, data collection methods for disaster risk assessment purposes have evolved over the years due to technological advances and innovations. With the abundance of available data collection methods, various stakeholders and end-users face the challenge of selecting the optimal strategy for surveying their building portfolio(s) of interest. Hence, this study seeks to develop an MCDM framework for choosing an optimal survey approach. The proposed MCDM framework recognizes that irrespective of the advantages of alternative data collection methods, it is essential to factor in the potential subjective detriment or disadvantage of adopting each data collection method for a given building class, location, and application. As discussed in several studies, an important aspect and challenge of a data collection exercise is the acceptance of alternative data collection techniques by decision-makers, considering the pros and cons of each method. The MCDM framework presented subsequently in this paper aims to address those challenges.

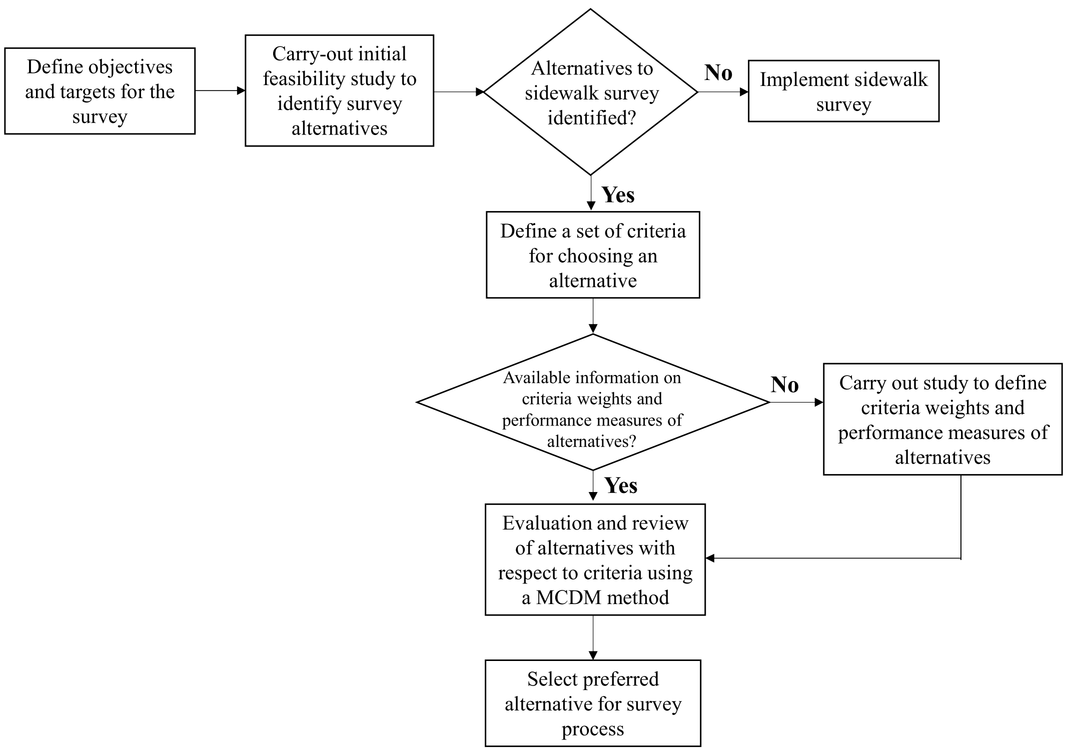

Fig. 1. The proposed framework for selecting the appropriate survey technique.

3. Proposed multicriteria decision-making framework

This section proposes a practical framework that various end-users (e.g., (re-)insurance firms, business investors, and local authorities) can adopt when choosing a suitable data collection technique for medium-to-large building portfolios. As recommended in FEMA P-154 [1], it is expected that the (re-) insurance firms, business investors, or local authorities have a program manager to oversee the survey process and a supervising engineer to provide the technical expertise necessary to conduct the survey program. Furthermore, the manager and supervising engineer are expected to have sufficient background knowledge on various survey alternatives. The proposed framework is schematically presented in Fig. 1. Specifically, the flowchart in Fig. 1 describes the various steps in selecting an optimal survey technique. The framework consists of two main phases. The initial phase is the planning stage which entails the definition of aims and scope of the survey (data collection) process and a feasibility study to identify data collection alternatives based on a number of objectives (e.g., desired cost level, the urgency of data needs, level of health and safety, and desired data reliability to achieve the aims of data needs). The second phase is the analysis phase, where an MCDM method is used to select the optimal survey technique. Each of the steps in the framework is described below.

3.1. Definition of survey aim, scope and objectives

As a first step, end-users need to define the aims of the data collection exercise (e.g., development of exposure database for catastrophe risk modeling) and scope (e.g., which building classes within the portfolio are of interest, desired information resolution for each building class in the portfolio). If possible, the involved decision-makers may forecast other potential future use of the collected data. They are also expected to be aware of the potential natural hazards affecting the considered area/community and whether a suitable data collection form (hard or digital) has been developed for the program. Depending on the program scope and potential use of the data, end-users can also decide if the survey of building interiors is required for a significant proportion of the building portfolio (e.g., in cases where the lateral load-resisting system cannot be identified from an exterior survey due to architectural finishes). This will help identify candidate data collection approaches required to achieve the project's desired results.

In some instances, decision-makers may be interested in varying resolution levels of the building information for different building types. For example, one may be interested in extensive/detailed surveys for critical infrastructure/strategic assets (e.g., hospitals) to develop refined structural/non-structural models. In contrast, other less extensive methods may be sufficient for residential/ordinary buildings. Therefore, an initial classification of the building portfolio based on the asset occupancy/function may be carried out to divide the buildings into classes based on desired resolution levels.

3.2. Initial feasibility study to identify survey alternatives

During the initial feasibility study, it is expected that end-users have an idea of the project constraints (i.e., available financial, human, time, and technological resources). Therefore, the main aim of the initial feasibility study is to identify candidate survey approaches that can be implemented to achieve the project aim and scope, given the project constraints.

During this step, it may be essential to identify and quantify the degree of homogeneity in each defined building class. For example, if the residential buildings in a to-be-surveyed estate are all similar and specific information on each building is not important to the potential data use, a sidewalk survey of a few buildings, combined with GIS information of the buildings in the estate, may be sufficient to develop the building inventory. In such a case, the analysis phase of the framework is not needed.

Candidate survey techniques are identified depending on the aims, specific objectives, scope, and constraints. Candidate techniques can be one of the techniques previously described or a hybrid one (i.e., a combination of methods). It is noteworthy that end-users can also consider different survey approaches for different building classes. Also, knowing project constraints, some potential survey techniques can be easily discarded. For example, drone deployment could be considered infeasible due to aerodrome flight restrictions, budget constraints, insufficient technical know-how, and inadequate resources to train people to use drones. Likewise, a conventional sidewalk survey could also be deemed infeasible and eliminated from the list of candidate survey approaches for health and safety reasons (and related restrictions) during a severe global pandemic, as demonstrated by COVID-19.

As part of the feasibility study, data acquisition, management, and quality control plans need to be developed. For example, a self-upload image-acquisition plan could entail a program requiring homeowners to upload photos of their houses when completing their online census form or liaising with real estate agencies to provide information on client homes. Also, end-users need to have a feasible plan for adequate management (e.g., data storage) of the collated information to avoid an undesirable data breach. Furthermore, data privacy issues need to be accounted for during the feasibility study for ethics-related reasons.

Table 1
Evaluation criteria selection for selecting an optimal survey technique.

Group	Criteria	Category
Monetary factors	C_1: Cost incurred on preparation	Cost
	C_2: Cost incurred on equipment and consumables	Cost
	C_3: Cost incurred on training screeners	Cost
	C_4: Travel cost to and within the survey area	Cost
Person-Time factors	C_5: Travel time between surveyed buildings	Cost
	C_6: Average inspection time for each building	Cost
	C_7: Person-days of preparation time (including training)	Cost
Risk factors	C_8: Health and safety risk	Cost
Quality assurance	C_9: Technique effectiveness	Benefit

3.3. Defining criteria for decision making and criteria weights

A set of evaluation criteria needs to be defined after the subset of candidate survey techniques has been selected. It is essential to only consider criteria that may significantly influence the selection of an optimal survey technique. A criterion for decision-making can be classified as a benefit criterion or cost criterion. A criterion is classified as a benefit criterion if an increase in the corresponding indicator (or performance measure) results in a potential gain. In contrast, a criterion is classified as a cost criterion if an increase in the corresponding performance measure results in possible loss and vice versa.

The proposed criteria relevant for selecting an optimal survey technique are presented in Table 1. The criteria can be classified into four groups – monetary factors, person-time factors, risk factors, and quality assurance level. Appropriate consideration of monetary factors and quality assurance level of candidate survey techniques enable decision-makers to assess the trade-off between cost and data reliability.

Except for the quality assurance level, all the groups are cost criteria. As shown in Table 1, each group is made of one or more criteria that may significantly influence the selection of an optimal survey technique. The choice to separate the groups into different criteria is related to the fact that the weight coefficients (to be defined subsequently) for criteria in the same group may not be the same. Therefore, the adopted breakdown approach allows one to identify the critical criteria, rather than a group of criteria, influencing the decision making and may use this for further evaluation.

Regarding monetary factors, the preparation costs include any pre-field planning cost (e.g., hiring core staff, preliminary assessment of the to-be-surveyed region), cost of the development of data acquisition and processing strategy, among others. The cost incurred on equipment and consumables includes hardware, software, and stationeries acquired for the data collection project. These could include, for instance, drones, laser scanners, Hi-Viz jackets, GIS software, and image processing software. It is also noted that, depending on the survey technique, additional costs may be incurred for acquiring equipment for removing architectural finishes to enable surveyors to identify relevant structural typologies in buildings. Other costs are incurred on training the surveyors and traveling to and within the survey area/community.

The person-time factor includes time spent preparing for the survey technique, the average time to inspect a building (including time to complete data collection form and/or digitize data), and travel time to and between surveyed buildings.

The risk factor considers the likelihood of hazards and vulnerability of the surveyors during the process. This could include accident risks during travel, contracting diseases during a pandemic, and post-disaster cascading events (e.g., aftershocks).

Finally, the quality assurance factor quantifies the reliability of data collected using the considered technique. For example, if building dimensions are important, the data reliability of a laser scanner may be better than that of measures estimated from street-view images. The effectiveness of a survey approach relative to the sidewalk survey approach can be assessed using interrater reliability analyses [10] or a pedigree assessment framework [18].

It is noteworthy that aside from the criteria discussed above, decision-makers may consider any other region- or task-specific criteria not considered in this study.

As part of the evaluation process, criteria weights are defined for the criteria. Criteria weights express the relative importance of one criterion with respect to another in the amplification or de-amplification of the rating of each survey alternative and the selection of the optimal choice.

The definition of criteria weights often requires expert judgment and available information on the aims, specific objectives, and scope of the survey and potential use of the data. Hence, criteria weights may vary between survey programs if the aims of the programs or the potential use of the data from these programs are different.

Criteria weights can either be defined based on expert judgment or using the Analytical Hierarchy Process (AHP) [19]. In the AHP approach, an $n \times n$ pairwise comparison matrix (where n is the number of criteria) is defined through linguistic expressions of relativity using a nine-point scale, which are then associated with real numbers. If an expert prefers the importance intensity of a criterion C_j over another criterion C_k, the value c_{jk} is derived from a nine-point scale [19]. If the expert considers C_j and C_k equally important, c_{jk} equals unity. A c_{jk} value between two and nine expresses the expert judgment of the superiority of C_j over C_k. In contrast, a c_{jk} value between 1/9 and 1/2 expresses the expert judgment of the superiority of C_k over C_j. It is noted that c_{jk} is equal to the ratio between the weights of criteria C_j and C_k (i.e., w_j/w_k).

Once the pairwise comparison matrix is defined, a consistency check is carried out to verify if the defined c_{jk} are not entirely random. A pairwise comparison matrix is typically deemed acceptable if the calculated consistency ratio (CR) (Eq. (1)) is less than 10% [19]. If an unacceptable value of CR is calculated, the pairwise comparison matrix needs to be redefined.

$$CR = \frac{CI}{RCI} = \frac{\lambda_{max} - n}{n - 1} \cdot \frac{1}{RCI}, \tag{1}$$

where CI is the consistency index, RCI is the random consistency index and is defined as a function of n, λ_{max} is the maximum eigenvalue of the pairwise comparison matrix.

The criteria weights (w_j) are then developed from the first eigenvector (λ_{max}) of the pairwise comparison matrix C = [c_{jk}]. For brevity, full details on the AHP approach for defining criteria weights are not presented here. Instead, interested readers are referred to [19].

3.4. Defining performance measures for each alternative

After the criteria and criteria weights have been defined, the performance measure of each candidate survey technique for every criterion is defined. The definition of performance measures can be based on expert judgment, published literature, or other available data from field surveys. For example, FEMA P-154 provides a range of expected costs and time expended pre-field planning and during the field screening of buildings. Also, studies [6,10] provide performance measures for their proposed survey approaches. Finally, the defined performance measures are used to construct a decision matrix (See Table 2).

A preliminary study can be carried out if no information is available to define performance measures for a given candidate survey method/technique. This preliminary study entails deploying this survey approach on a subset of buildings within the building portfolio. The first step for this preliminary study is to identify and select buildings within the building portfolio for which the survey approach will be carried out. It is suggested that the number of buildings considered should be a proportion of total buildings within the considered area/community. Once the number of buildings has been identified, it is essential to ensure that all known archetype structures in the building portfolio are represented in the selected buildings. Subsequently, the survey approach is deployed on the identified buildings, and the performance measure for this alternative can be evaluated.

As previously mentioned, a candidate survey technique could combine two or more techniques. In such cases, the performance measure may be evaluated based on the contributing proportion of the two or more primary techniques to the secondary one (i.e., considering a weighted average). For example, considering the decision matrix in Table 2, if Technique *c* is an alternative using 70% of technique *a* and 30% of technique *b*, X_{13} may be taken as $0.7X_{11} + 0.3X_{12}$.

3.5. Multicriteria decision-making methods

MCDM methods are cross-disciplinary tools for evaluating and ranking potential alternatives based on multiple conflicting criteria. MCDM methods can either be classified as multi-objective decision-making (MODM) methods or multi-attribute decision-making (MADM) methods [20]. MODM deals with continuous optimization problems to evaluate an infinite set of continuous alternatives for which constraints are predefined in the form of vectors of decision variables.

On the other hand, MADM deals with a finite set of discrete alternatives. MADM techniques can be value function-based, reference point-based (or distance-based), outranking-based, or based on pairwise comparison methods [21]. Value function-based MCDM methods aggregate the normalized performance-measure values of the decision matrix, considering the associated criteria weights. Examples of value function-based MCDM methods include the additive Simple Weighting Method (SAW) [22], Weighted Aggregated Sum Product Assessment (WASPAS) [23], and Complex Proportional Assessment Method (COPRAS) [24].

Outranking MADM methods are approaches based on establishing a preference relationship on a subset of probable alternatives to indicate the hierarchy among the alternatives. Examples of outranking methods include the Preference Ranking Organization Method For Enrichment Evaluation (PROMETHEE) [25] and *ÉLimination et Choix Traduisant la REalité* (ELECTRE) (in English – ELimination and Choice Translating REality) [26,27].

Reference point-based or distance-based methods measure the distances among each probable alternative and a reference point (which could be an ideal or average solution). Examples of this method include the Evaluation based on Distance from Average Solution (EDAS) approach [28], the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) [20], Multicriteria optimization, and compromise solution (VIKOR) [29].

Pairwise comparison methods use the knowledge from the analyst/user in defining the criteria weights and comparing probable alternatives with respect to a criterion. Examples of pairwise comparison methods include the analytical hierarchy process (AHP) [19], Analytic Network Process (ANP) [30], Measuring Attractiveness by a Categorical Based Evaluation Technique (MACBETH) [31].

It is noteworthy that identifying the most suitable MCDM method for decision-making is still an ongoing research topic. Studies [32–35] have discussed methodologies for identifying the most suitable MCDM method. For the sake of brevity, these methodologies are not discussed here. Instead, interested readers are referred to the studies mentioned above for more information.

3.6. Accounting for the influence of the selected MCDM method, uncertainties in performance measures and criteria weights on decision making

There is an element of randomness during any decision-making process which originates from uncertainties in the factors being considered in the analysis. The MCDM methods previously discussed in this paper are typically deterministic methods that assume the criteria weights and performance measures are deterministic parameters. However, sensitivity analyses [33] have shown that changes in criteria weights and performance measures can result in different decision-making outcomes. Also, studies [36] have shown that different MCDM methods can result in different outcomes in many practical applications – i.e., for the same set of probable performance measures and criteria weight, different alternative rankings may be evaluated. To account for the likelihood of variability in the alternative ranking, a probabilistic MCDM approach can be adopted. It is noteworthy that a probabilistic MCDM approach may be

Table 2
Defining the decision-making matrix.

Criteria	Weights	Candidate survey techniques			
		Technique a	Technique b	Technique c	Technique d
		1	2	3	m
C_1	w_1	X_{11}	X_{12}	X_{13}	X_{1m}
C_2	w_2	X_{21}	X_{22}	X_{23}	X_{2m}
C_3	w_3	X_{31}	X_{32}	X_{33}	X_{3m}
…	…	…	…	…	…
C_n	w_n	X_{n1}	X_{n2}	X_{n3}	X_{nm}

helpful in cases where there is no consensus amongst decision-makers on the suitable MCDM technique, criteria weights and/or performance measures.

Initial studies [37] on uncertainty propagation in MCDM incorporated fuzzy sets [38] in dealing with subjective uncertainty. More recently, studies [36] have considered parameter uncertainty (i.e., uncertainty in criteria weights and performance measures) as part of sensitivity analyses in MCDM. However, the treatment of method-to-method uncertainty is not properly considered in such studies. The current study builds on the effort of these aforementioned studies. In the current study, three primary sources of uncertainties in an MCDM framework, namely:

- Method-to-method uncertainty is an epistemic uncertainty resulting from the possibility of different MCDM methods providing a different hierarchy. As earlier mentioned, studies have shown that different MCDM methods can result in different outcomes. This variability is attributed to different mathematical assumptions and operations adopted by these methods. Hence, the issue of identifying the most suitable MCDM method for a particular case still exists.
- Uncertainty in the performance measure matrix X results from epistemic and aleatory uncertainties in quantifying the performance measure (e.g., time and cost) of survey alternative i with respect to criterion j. For example, the actual costs for purchasing equipment or traveling costs may deviate from the expected costs in a favorable or an adverse direction. Each element X_{ij} of the performance matrix represents the performance measure of the survey alternative i with respect to criterion j with $i = 1, 2, \ldots, n$ and $j = 1, 2, \ldots, m$, where n is the total number of survey alternatives and m is the number of criteria for decision making.
- Uncertainty in weight coefficients for each criterion j is a result of epistemic uncertainty in the subjective judgment of decision-makers in the development of the pairwise comparison matrix using the previously mentioned nine-point scale (i.e., quantifying the importance intensity of a criterion C_j over another criterion C_k). In the deterministic MCDM, it is assumed that the decision-makers agree on each coefficient c_{jk}.

This study proposes a simple approach to treating the uncertainties mentioned above. A flowchart for the proposed approach is presented in Fig. 2. An initial step of the framework is assessing the need to consider method-to-method uncertainty. The treatment of method-to-method uncertainty in the framework is only relevant when two or more preferred deterministic MCDM approaches result in different rankings. If preferred deterministic MCDM methods agree in their ranking, treating model-to-model uncertainty may not be important. However, it is noteworthy that stochastic MCDM methods may disagree on the optimal solution (even when the deterministic MCDM methods agree) in cases where the utility scores for the MCDM methods are close, such that variability in criteria weights can result in disagreements between them the MCDM methods.

For each preferred MCDM method M_k (where $k = 1, \ldots, l$), Monte Carlo sampling is repeated for a selected optimum sample size S. Studies [39] have shown that 10,000 simulations are sufficient to produce stable results. However, it is recommended that a sensitivity

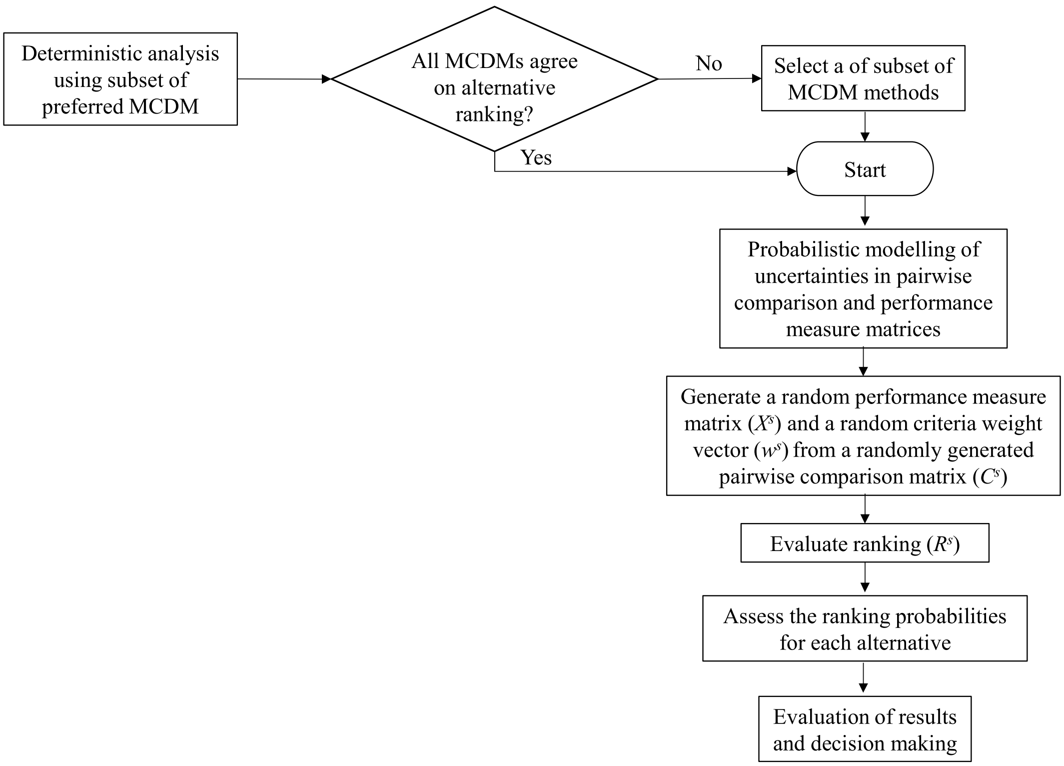

Fig. 2. The probabilistic procedure to treat method-to-method uncertainties and uncertainties in performance measures and criteria weights.

analysis is carried out to assess the stability of the results before selecting a sample size, as this depends on the variability of the considered parameters for the specific problem.

The uncertainty in the performance measure matrix is propagated by representing each element X_{ij} of the matrix with their mean $\overline{X}_{ij}$ and standard deviation $\sigma_{X_{ij}}$ (See Fig. 3). The distribution model for each element X_{ij} is chosen based on engineering judgment or fitting a distribution to available data on the element. Typical distributions for X_{ij} are uniform, normal, lognormal, triangular, and PERT distributions [39,40]. Uniform distributions are defined if the information on the minimum and maximum cost or time estimates are available. Triangular distributions use lower, modal and upper limits for cost or time estimates. PERT distributions are constructed when the pessimistic, most likely, and optimistic cost estimates are available. Normal distributions are used if the information on only the mean and standard deviation of cost or time estimates are available, and zero skewness is expected. A normal distribution can assume negative values, which may not be appropriate in some cases. In such cases, a lognormal distribution would be preferable. For each iteration s (where $s = 1,2, \ldots, S$), a random performance measure matrix $\overline{X}^s$ is generated based on the considered distribution model and its parameters.

Uncertainty propagation in the pairwise comparison matrix C and the corresponding weight vector w *is* treated using a stochastic analytic hierarchical process (SAHP) [41]. The probability distribution function of each element c_{jk} below the diagonals pairwise comparison matrix C is evaluated from the subjective judgment of each decision-maker (as previously described in this paper). The distribution function element c_{jk} corresponds to the level of agreement in the subjective judgment of the decision-makers. When decision-makers do not agree, c_{jk} is uniformly distributed over the range of the maximum and minimum value of c_{jk} provided by the decision-makers. For example, the judgment of a group of decision-makers on the importance intensity of a criterion C_j over another criterion C_k could be equally split on a scale of 3, 4, 5, and 6. In such a case, the random variable c'_{jk} is uniformly distributed over the range [3,6]. When decision-makers agree, the distribution function transitions into a triangular distribution. In this case, the modal value could either be at the center of the range (symmetric triangular distribution) or anywhere else (skewed triangular distribution).

To develop a random pairwise comparison matrix C^s for iteration s, using the defined probability distribution model, random values of c'_{jk} are generated using Monte Carlo sampling; c'_{kj} is calculated as $1/c'_{jk}$. It is noteworthy that c'_{jj} is taken as unity in each realization. For each random pairwise comparison matrix C^s for iteration s, a consistency check is run for each randomly generated pairwise comparison matrix (i.e., calculated consistency ratio (CR) is less than 10%). The random weight vector w^s is then generated from each random pairwise comparison matrix C^s (Fig. 3).

The MCDM analysis is carried out using a random weight coefficient w^s and random performance measure matrix X^s for a total of S times. The ranking of each alternative is stored for each simulation, and, at the end of the S simulations, a frequency distribution

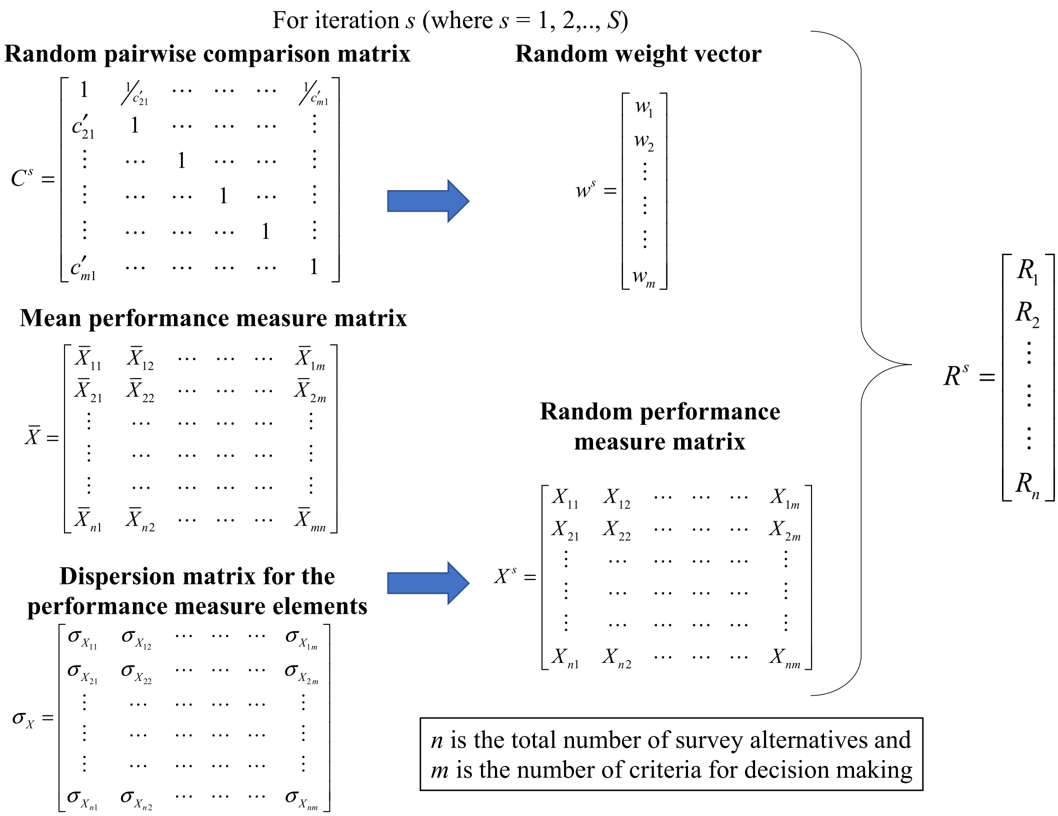

Fig. 3. Generation of random criteria weight matrix (w^s), random performance measure matrix (X^s), and random alternative ranking (R^s) for iteration s ($s = 1,2,..,S$).

expressing the likelihood of an alternative having a ranking composition R_i is computed. For example, for a given MCDM method M_k, an alternative i has a probability of $p_i(M_k)$ of being ranked in the first position.

Each MCDM method M_k is associated with a weight coefficient wc_k based on how the decision-makers perceive the adequacy of the considered method. The MCDM method considered to have the best adequacy has the highest weight coefficient. For the considered MCDM methods, the probability of alternative i being ranked the optimal alternative is given as:

$$P_i = \sum_{k=1}^{l} wc_k p_i(M_k) \tag{2}$$

The alternative with the highest P_i is considered the optimal alternative.

4. Application of framework to a case-study building portfolio

4.1. Overview of the case study

The applicability of the proposed framework is demonstrated using a case-study building portfolio located in a hypothetical synthetic city, hereafter referred to as 'Hazardville', susceptible to earthquake and tsunami. Hazardville comprises two major zones – residential and business (Fig. 4). The residential zone, divided into four sub-zones, is assumed to be a large portfolio of 12,000 houses, with number of stories ranging from one to four. It is further assumed that all the buildings in the residential zones are made of reinforced concrete frame structures with masonry infills. In terms of building age, it is assumed that 65% of the buildings are pre-1970s structures designed with inadequate seismic provisions. The centrally-located business zone is assumed to be a small-medium portfolio of 1,200 buildings. The central location of the business zone allows easy access for the residents of the residential zones. The number of stories of buildings in the business zone ranges from four to fifteen. It is further assumed that there is a wide range of building typologies (e.g., type and material of structural and non-structural systems, design era, and retrofit history).

The local authority of Hazardville aims to survey its building inventory. As set out by the local authority, the potential use of the data entails developing building inventory for community-level multi-hazard damage and loss impact assessments and developing an in-house building-specific and community-level post-earthquake response-enhancing tool. It is assumed that local authority intends to adopt existing rapid visual survey forms [1,10] to gather information on hazard proximities, the number of stories, floor area, building shape, type and material of structural and non-structural systems, presence of interior or external staircases, presence and average location of window and door openings, and presence and characteristics of vertical wave barriers (e.g., fences) around the buildings.

To satisfy the project's aim, the local authority is interested in identifying the optimal survey technique for the residential and business zones to achieve the aims and objectives of the survey exercise. Therefore, three alternatives were considered aside from the traditional sidewalk survey (T1). The first alternative (T2) is the mixed-mode survey approach presented in Opabola et al. [10]. The second alternative (T3) is the combination of GIS, GPS, digital video from moving vehicles, and information from a past census similar to that described in Montoya [5]. Finally, the third alternative (T4) is the use of terrestrial laser scanners (TLS) similar to that described in existing literature [16,17].

4.1.1. Residential zone

In this case study, it is assumed that a preliminary survey by the local authority suggests a high level of homogeneity in the portfolio (i.e., in terms of construction materials, lateral-load resisting system, number of stories, and design era). For such a extensive portfolio, with a high level of homogeneity, the objectives set by the local authority for a candidate survey include low cost, low completion time frame, a high level of health and safety concerns due to a pandemic, and good data reliability.

A suitable pairwise comparison matrix is developed to derive the weight coefficients for the considered nine criteria in Table 1. It is assumed that the decision-makers are interested in a low-cost technique that can be completed in the shortest time. Also, the decision-makers hold a strong preference for a technique with minor health and safety concerns. The calculated criteria weights for the pairwise comparison matrix are presented in Table 3. As shown in Table 3, the largest weight is attached to 'health and safety risk'. Data reliability and cost incurred on equipment are considered to have equal importance. Travel costs and time, inspection time, and

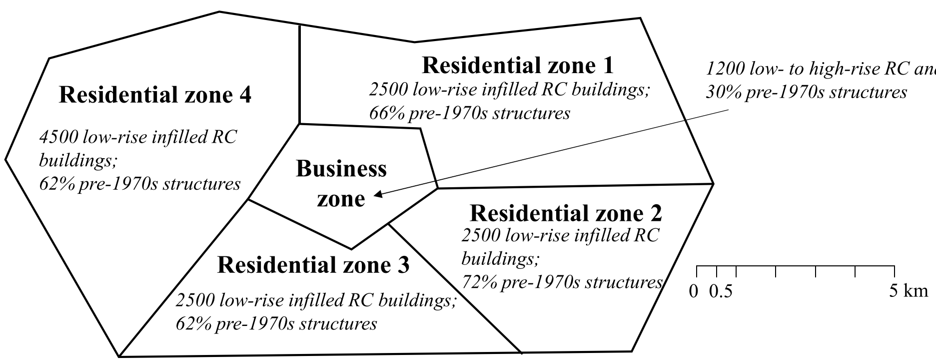

Fig. 4. Landmark of hazardville.

preparation time have the least criteria weights. A consistency ratio CR of 4.2% was calculated using Eq. (1).

The performance measure coefficients relating each survey alternative to the nine criteria are derived mainly based on published literature and the authors' field experience. The average inspection time for a sidewalk survey is assumed to be 20 min. This value was taken as the average of the 15–30 min range discussed in FEMA P-154. Based on the remote survey information presented in Opabola et al. [10], the remote survey consumes at least 30% less time than the sidewalk. Hence, this study assumes that the average inspection time for a sidewalk survey is 14 min. The timeframe for laser scanning buildings can range from 30 min to a couple of hours, depending on the size of the building, the number of scanners, and the scanning rate of the scanners [42–44]. Given that the TLS would be set up for both exterior and interior, for the purpose of this study, it is assumed that the available TLS devices can carry out a building survey in an average of 40 min. The normalized inspection time relative to the sidewalk for each candidate survey approach is presented in Table 3. A similar approach was adopted in defining the cost criteria (i.e., C_1, C_2, C_3, and C_4) in Table 3. The data for the costs of a sidewalk survey are based on the values presented in FEMA P-154. The cost data for T2 are based on the authors' experience. Information on the costs for the TLS survey is based on data available in published literature (e.g., Ref. [42]).

The travel time between surveyed buildings is dependent on the size of the considered zones. This study used a simple approach to provide normalized travel time relative to the sidewalk for each candidate survey approach. For the remote survey, there is no time travel time between buildings. However, a minimal amount of time might be required to assess the satellite and street-view imagery for the buildings. In this study, we conservatively assume this time is equal to 10% of the time required for travel between buildings by field assessors. For T3, it is assumed that the digital video data collection process will reduce travel time by about 50%. For the TLS, we consider the time for set-up and demolition of the laser scanners between buildings and the transportation of the devices and assessors. It was decided to assume that the travel time between buildings for T4 is similar to T1.

Data reliability for T2 is based on the inter-class coefficient (ICC) computed from an inter-rater reliability analysis for remote surveys discussed in Opabola et al. [10]. While Opabola et al. [10] reported an ICC value of 0.9 for school buildings, we conservatively assume an ICC of 0.8 in this study. This conservativism is deemed appropriate given the wide range of building configurations assumed to exist in Hazardville. We further assume that data from T4 would be more reliable than the sidewalk survey because the TLS gathers detailed information on the interior parts of the building, including the structural dimensions. By assuming the TLS survey can provide accurate results on structural dimensions and conditions of a building, using the process described in Ref. [10], inter-rater reliability analysis for the sidewalk survey and TLS survey for the interior and exterior parts of a building was used in computing an ICC value of 0.22. Hence, we assumed a value of 4.5 (i.e., 1/0.22) for the data reliability of the TLS survey relative to the sidewalk survey (Table 3).

The normalized performance measures relative to the sidewalk for each candidate survey approach are presented in Table 3.

Three MCDM methods were considered in this study – TOPSIS, EDAS, and WASPAS. Table 4 shows the results of the deterministic MCDM analysis using the three methods. As shown in Table 4, all three methods agree that T2 is the optimal survey approach for the residential zone. Furthermore, stochastic MCDM was carried out using the methodology discussed previously. For the stochastic MCDM, purely for demonstrative purposes, it is assumed that each performance measure for T2, T3, and T4 are lognormally distributed with a standard deviation of 0.5. It is noted that the standard deviation is non-dimensional because the performance measures are normalized. The standard deviation of T1 is set as zero. This was done in order to keep each performance measure coefficient of T1 as unity always. For the pairwise comparison matrix, it is assumed that all coefficients are uniformly distributed with a lower and upper bound of ± 3.

Table 4 shows the results of the stochastic MCDM analysis using the methodology presented in Fig. 2. As shown in the Table, both EDAS and WASPAS rank T2 as the optimal approach with a probability of about 85%. On the other hand, TOPSIS ranks T2 as the optimal approach with a probability of 65%. Given that all the MCDMs agree on the ranking, method-to-method uncertainty is not influential here. Also, for the residential zone, the influence of uncertainties in the performance measure matrix and weight coefficients is not significant enough to cause a shift in the rank preference between the deterministic and stochastic classifications for each method (Table 4).

4.1.2. Business zone

The majority of buildings in the business zone of Hazardville are considered to be critical facilities (e.g., hospitals, designated vertical evacuation structures for tsunami, police station, fire and rescue station). It is also assumed that a preliminary survey by the

Table 3
Decision-making matrix for the residential zone.

Criteria	Weights	Performance measures (Median)			
		T1	T2	T3	T4
		1	2	3	4
C_1: Cost incurred on preparation	0.07	1	0.7	0.8	2
C_2: Cost incurred on equipment and consumables	0.14	1	0.6	1.2	2.5
C_3: Cost incurred on training screeners	0.08	1	0.5	0.8	1.3
C_4: Travel cost to and within the survey area	0.04	1	0.1	0.4	1.5
C_5: Travel time between surveyed buildings	0.04	1	0.1	0.5	1
C_6: Average inspection time for each building	0.04	1	0.7	0.7	2
C_7: Person-days of preparation time (including training)	0.05	1	0.7	0.8	2
C_8: Health and safety risk	0.38	1	0.3	0.4	0.7
C_9: Data reliability	0.16	1	0.8	0.8	4.5

Table 4
MCDM output for the residential zone.

s/no	Deterministic rank classification			Stochastic classification (likelihood of each approach being ranked as the optimal approach) [%]		
	TOPSIS	EDAS	WASPAS	TOPSIS (Rank)	EDAS (Rank)	WASPAS (Rank)
T1	4	4	4	0 (4)	0 (4)	0 (4)
T2	1	1	1	64.6 (1)	85.5 (1)	87.9 (1)
T3	2	2	2	20.9 (2)	12.5 (2)	11.1 (2)
T4	3	3	3	14.5 (3)	2 (3)	1 (3)

local authority suggests a low level of homogeneity in the portfolio. Given the importance level of the facilities in this zone and the low level of homogeneity, the targets set by the local authority for a candidate survey include minor constraints on cost and completion time frame, moderate level of health and safety concerns, and highest possible data reliability.

Similarly, a suitable pairwise comparison matrix was developed, using the aforementioned objectives of the local authorities, with a consistency ratio of 6.1%. The calculated criteria weights for the pairwise comparison matrix are presented in Table 5. Table 5 shows that the largest weight is attached to 'data reliability'. In comparison with Building class 1, the criteria weight for 'cost incurred on equipment and consumables' is reduced for Building class 2.

In addition to the three alternatives considered for the residential building class, we consider a fourth alternative of combining T2 and T4 for the business zone. It is assumed that the local authorities are interested in exploring the feasibility of adopting T2 and T4 for 65% and 35% of the building portfolio, respectively. As previously discussed in this paper, each performance measure coefficient of T5 X_{n5} is taken as $0.65X_{n1} + 0.35X_{n4}$. For simplicity, we adopt similar relative performance measure coefficients for both residential and business zones (Table 5). It is further assumed that the probability distributions for the pairwise comparison and performance measure matrices for the business zone are the same as those of the residential zone.

Table 6 shows the results of the deterministic MCDM analysis for the business zone. As shown in Table 6, the deterministic rankings of the five techniques vary across the three considered MCDM methods. This reinforces the need to consider method-to-method ranking variability in stochastic MCDM analysis. Table 6 shows the results of the stochastic MCDM analysis using the methodology presented in Fig. 2. As shown in the Table, the influence of uncertainties in the performance measure matrix and weight coefficients causes a shift in the rank preference between the deterministic and stochastic classifications for each method. For example, T4 was ranked second and first by the deterministic and stochastic EDAS, respectively.

For the purpose of this study, we assume that the decision-makers have similar confidence levels for all three MCDM methods. Hence a weight coefficient wc_k of 1/3 is assumed for each of the three methods. By adopting Eq. (2), the final stochastic classification is presented in Table 6. T4 is ranked as the optimal survey technique by the stochastic classification (in agreement with deterministic TOPSIS and WASPAS). T5 is ranked second by the stochastic classification in agreement with deterministic TOPSIS). It is noted that the ranking based on the stochastic method could change depending on the considered wc_k.

Using the MCDM framework, given the aims, objectives, and scope of the local authorities of Hazardville, survey approaches T2 and T4 are recommended for the residential and business zones of Hazardville, respectively.

5. Conclusions

In recent times, technological advancements and innovations have led to the development of various pre- and post-earthquake data collection alternatives to the traditional sidewalks using remote sensing, global positioning systems (GPS), digital video/photography, unmanned aerial vehicle (UAV) systems, and geographic information systems (GIS). Hence, decision-makers may face the challenge of selecting the optimal survey approach (or a combination of approaches) that satisfies the aim and scope of their building inventory development and analysis. Selecting a suitable survey approach requires developing a multicriteria decision-making (MCDM) framework. This study developed an MCDM framework for selecting the optimal survey approach for building portfolios.

The main inputs for an MCDM analysis are criteria weights and corresponding performance measure coefficients. Four criteria groups were considered to be important in selecting an optimal survey approach – monetary factors, person-time factors, risk factors,

Table 5
Decision-making matrix for Business zone.

Criteria	Weights	Performance measures (Median)				
		T1	T2	T3	T4	T5
		1	2	3	4	5
C_1: Cost incurred on preparation	0.07	1	0.7	0.8	2	1.2
C_2: Cost incurred on equipment and consumables	0.09	1	0.6	1.2	2.5	1.3
C_3: Cost incurred on training screeners	0.07	1	0.5	0.8	1.3	0.8
C_4: Travel cost to and within the survey area	0.04	1	0.1	0.4	1.5	0.6
C_5: Travel time between surveyed buildings	0.04	1	0.1	0.5	1	0.4
C_6: Average inspection time for each building	0.04	1	0.7	0.7	2	1.2
C_7: Person-days of preparation time (including training)	0.04	1	0.7	0.8	2	1.2
C_8: Health and safety risk	0.14	1	0.3	0.4	0.7	0.4
C_9: Data reliability	0.47	1	0.8	0.8	4.5	2.1

Table 6
MCDM output for Business zone.

s/no	Deterministic rank classification			Stochastic classification (likelihood of each approach being ranked as the optimal approach) [%]				
	TOPSIS	EDAS	WASPAS	TOPSIS (Rank)	EDAS (Rank)	WASPAS (Rank)	Updated ranking	
							Eq. (2)	Rank
T1	5	5	5	0 (5)	0 (5)	0 (5)	0	5
T2	3	3	2	0.4 (4)	9.6 (3)	26.1 (3)	12	3
T3	4	4	4	0.9 (3)	4.1 (4)	2.7 (4)	2.6	4
T4	1	2	1	76 (1)	44.6 (1)	44.0 (1)	54.9	1
T5	2	1	3	22.7 (2)	41.7 (2)	27.2 (2)	30.5	2

and data quality assurance. It is noteworthy that aside from the criteria discussed above, decision-makers may consider any other region- or task-specific criteria not considered in this study.

In the proposed framework, the criteria weights are evaluated from pairwise comparison matrices using the Analytical Hierarchical Process (AHP). Furthermore, to account for aleatory and epistemic uncertainties in MCDM, a stochastic MCDM framework is presented. The stochastic MCDM framework accounts for method-to-method uncertainty, uncertainty in the performance measures, and uncertainty in the criteria weights.

The application of the proposed deterministic and stochastic MCDM framework was demonstrated for a portfolio of 12,000 residential and 1,200 commercial buildings in a hypothetical multi-hazard prone region. The results suggested that informed decisions on identifying an optimal survey approach for various building categories could be efficiently derived using MCDM. Future studies can further demonstrate the practicability of the proposed framework using real-life assets/infrastructure.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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