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Seismic Risk Analysis of Hospital Buildings: A Novel Interval-Valued Spherical Fuzzy ARAS

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Abstract: Hospitals are vital infrastructures, but they can be particularly susceptible if located in an earthquake-prone area. Estimating the performance and projected damage of these structures in the event of future earthquakes is critical to minimize physical damage and disruption of surgery, rehabilitation, laboratory services, and other medical care operations. A quick and low-cost pre-assessment of the sensitivity of these structures will help hospital managements prepare for suitable retrofitting and reconstruction. On the other hand, a seismic risk assessment requires constructing a model that can offer expert opinions in a quantitative, methodical, and quantifiable way while still reflecting the uncertain and imprecise character of the process. This paper proposes a new decision support model by extending Additive Ratio Assessment (ARAS) with interval-valued spherical fuzzy sets. The study includes sensitivity and comparison analyses, practical implications, limitations, and future research avenues. The applicability of our methodology demonstrated a numerical example for assessing the seismic risk levels of hospital buildings.

Keywords: MCDM; Interval-valued Spherical Fuzzy Sets; ARAS; Hospital Building Risk Assessment

1. Introduction

Hospitals are essential components of a healthcare system. Their position is especially more vital after a catastrophe, such as an earthquake, since they must give medical and surgical treatment as well as nursing care to ill or wounded individuals [1]. In the case of an earthquake, hospitals must be fully functioning to safeguard patients and healthcare staff, as well as to give emergency care and medical treatment to patients who are driven to healthcare facilities. According to assessments undertaken after big earthquakes, hospital performance and functioning are connected not just to structural damage but also to damage to nonstructural materials and medical equipment [2].

Hospitals, unlike many other service buildings, have complex and diverse structures. The analysis of the earthquake behavior of these structures, which contain offices, dormitories, conference rooms, and social areas, as well as operating rooms, chemical and biological laboratories, and medical warehouses, is a time-consuming and costly process. A practical methodology of assessing the seismic sensitivity of hospital buildings would enable the efficient use of financial resources for future planning of potential retrofitting and rebuilding plans.

In this context, seismic risk level assessment of hospital buildings can be considered as a decision-making problem with inherent uncertainties such as vague expert evaluations, complicated qualitative and quantitative data, and ambiguous data relationships [3]. On the other hand, multi-criteria decision-making (MCDM) models are widely used to rank alternatives from a pool of candidates based on a set of criteria. Uncertainty, on the other hand, is a part of the actual world, and it is inherent in most MCDM problems. The criteria are usually qualitative, and decision-makers may be unclear about their assessments and can only evaluate them through linguistic terms, and fuzzy systems give appropriate ways to convert linguistic assessments of decision-makers to a numerical form and model the uncertainty in these problems.

Spherical fuzzy sets [4] are one of the recent extensions of ordinary fuzzy sets and provide users the opportunity to express their membership, non-membership, and hesitancy degrees independently, and in a spherical volume. Interval-valued spherical fuzzy sets [5] on the other hand, provide more space than the first generation for modeling the fuzziness in the problems.

1.1. Related Work

Additive Ratio Assessment (ARAS) [6] is an MCDM method that evaluates the performance of selected alternatives based on the comparison of each one with the ideal best alternative through a utility function. Many academics favor fuzzy ARAS approaches to handle problem-solving situations. Karagoz et al. [7] suggested an interval type-2 fuzzy ARAS for selecting a location for a recycling facility. Jaukovic et al. [8] combined Pairwise Relative Criteria Importance Assessment (PIPRECIA) and interval-valued valued triangular fuzzy ARAS and evaluated online learning courses. Moreover, Heidary et al. [9] integrated data envelopment analysis with ARAS in a triangular fuzzy environment and ranked human resource practices, and Buyukozkan and Guler [10] proposed a Simple Additive Weighting (SAW) ARAS model for smartwatch assessment by utilizing hesitant fuzzy sets to model the uncertainty. On the other hand, Yildirim and Mercangoz [11] worked for a hesitant fuzzy Analytical Hierarchy Process (AHP) ARAS model to evaluate logistics performances of countries, and Gul [12] studied Fermatean fuzzy sets to provide a SAW ARAS Viekriterijumsko Kompromisno Rangiranje (VIKOR) model with an application for selecting a pandemic testing laboratory.

Interval-valued spherical fuzzy sets have been increasingly used in various decision-making problems. Gul and Ak [13] proposed an interval-valued spherical fuzzy Order Preference by Similarity to Ideal Solution (TOPSIS) and evaluated a marble manufacturing facility, and Aydin and Gundogdu [14] developed a Multi-Objective Optimization by a Ratio Analysis plus the Full Multiplicative Form (MULTIMOORA) model and ranked performances of companies. Duleba et al. [15] worked for an AHP methodology to assess public transportation, and Jin et al. [16] presented an Organization, Rangement Et Synthese De Donnes Relationnelles (ORESTE) method for ranking quality characteristics. Moreover, Lathamaheswari et al. [17] introduced some new operators for interval-valued spherical fuzzy sets and selected a station for air quality analysis. A complete and systematic literature review of recent and state-of-the-art studies on spherical fuzzy studies can be found in the study of Ozceylan et al. [18].

In the context of earthquake-related problems, several MCDM models have been proposed. Adafer and Bensaibi [19] developed a seismic vulnerability assessment method for roads and quantified the criteria that affect the seismic behavior of roads with an AHP model. Jena et al. [20] evaluated earthquake vulnerability assessment by using an AHP VIKOR model, and Kumlu and

Tudes [21] used AHP TOPSIS for determining earthquake-risky areas. Cremen and Galasso [22] proposed a general MCDM model and studied a decision-making problem for an earthquake early warning system of a school. Alizadeh et al. [23] assessed the seismic vulnerability of residential houses by utilizing the AHP technique. Tyagi et al. [24] used AHP to evaluate the landslide hazard index to be used in a landslide hazard zonation map. In addition, Zhang et al. [25] investigated the effects of fault rupture on seismic responses of highway bridges band utilized a TOPSIS Weighted Sum Model (WSM) method for optimizing the fault crossing angle. The above-mentioned authors did not consider uncertainty and presented their works in a crisp environment.

The following gaps have been identified as a result of the completed review of the aforementioned research:

- The ARAS method has not benefited from interval-valued spherical fuzzy sets for addressing the vagueness.
- The nature of decision-making problems is unclear, which may have a substantial impact on the outcomes. However, the majority of previous earthquake-related MCDM approaches either ignored uncertainty and used crisp integers or only used two-dimensional fuzzy sets.
- The examination of seismic risk assessment of hospital buildings has received little attention. No previous research provides a model for prioritizing hospital buildings in terms of their seismic risk levels.

Around earthquake-related MCDM investigations, little has been done in terms of establishing sensitivity and comparative analyses.

1.2. Motivation and Contribution

The major goals of this research are to fill the gaps mentioned above, offer a novel decision support model, and handle a seismic risk evaluation problem. The fuzziness is modeled with interval-valued spherical fuzzy sets, and the alternatives are prioritized by using the ARAS technique. This work offers a novel approach by providing an interval-valued spherical fuzzy ARAS and evaluating the seismic risk assessment of hospital buildings in an MCDM structure while modeling the vagueness of experts by using fuzzy logic theory.

The rest of the paper is organized as follows: Section 2 presents the methodology as follows: First, the structure of traditional ARAS methodology which forms the backbone of the model is given, then mathematical operations of interval-valued spherical fuzzy sets, which are the building elements of the methodology, are summarized. Finally, the proposed interval-valued spherical fuzzy ARAS method is presented in a step-by-step form. In Section 3, the application is presented as follows: First, the criteria are introduced, then the numerical solution is provided, and finally, sensitivity, comparative and rank reversal analyses are given for further discussion. The paper is finalized in Section 4 with practical implications, limitations, and future research avenues.

2. Methodology

ARAS method evaluates the performance of selected alternatives and compares the scores of those selected alternatives with the ideal best alternative [6]. In this section, the interval-valued spherical fuzzy ARAS model is developed based on the definition, basic operators, and the linguistic scale presented for interval-valued spherical fuzzy sets.

2.1. Classical ARAS

A decision matrix X is defined with n criteria and m alternatives as shown in equation 1.

$$X = [x_{\mathrm{ij}}]_{\mathrm{mxn}} = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ x_{m1} & x_{n2} & \dots & x_{mn} \end{bmatrix} \quad (1)$$

where, x_{ij} is the performance value of the ith alternative with respect to jth criterion.

Normalization of decision matrix is obtained as equation 2 for beneficial criterion.

$$N_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \quad (2)$$

where N_{ij} is the normalized value of ith alternative. Normalization of decision matrix for cost criterion is obtained as follows:

$$x^*{}_{ij} = \frac{1}{x_{ij}} \quad (3)$$

$$N_{ij} = \frac{x^*{}_{ij}}{\sum_{i=1}^{m} x^*{}_{ij}} \quad (4)$$

Weighted normalized matrix W is obtained as in equation 5.

$$W = [d_{\mathrm{ij}}]_{\mathrm{mxn}} = \begin{bmatrix} d_{11} & d_{12} & \dots & d_{1n} \\ d_{21} & d_{22} & \dots & d_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ d_{m1} & d_{n2} & \dots & d_{mn} \end{bmatrix} \quad (5)$$

$$d_{ij} = N_{ij} \times w_j \quad (6)$$

where N_{ij} is the normalized; d_{ij} is the weighted normalized value of the ith alternative with respect to jth criterion, and w_j is weight of jth criterion.

Optimality value O_i for the ith alternative is obtained as in equation 7.

$$O_i = \sum_{j=1}^{n} d_{ij} \quad (7)$$

The degree of utility U_i for the ith alternative is obtained as in equation 8.

$$U_i = \frac{O_i}{O_o} \quad (8)$$

where, O_i is the optimality value for the ith alternative and O_o is the optimality value of the optimal alternative. The alternatives are ranked according to utility degrees as the highest is the best.

2.2. Interval-Valued Spherical Fuzzy Sets

A spherical fuzzy set ($\tilde{A}_S$) must satisfy the following condition:

$$0 \le \left(\mu_{\tilde{A}_S}(u)\right)^2 + \left(v_{\tilde{A}_S}(u)\right)^2 + \left(\pi_{\tilde{A}_S}(u)\right)^2 \le 1, \forall u \in U \quad (9)$$

where μ, v and π are the membership, non-membership, and hesitancy degrees, respectively. Interval-valued fuzzy sets were later developed and provide an increased fuzziness modeling capacity with an interval-type structure rather than a single point. Definition and basic operations [5] of interval-valued spherical fuzzy sets are given below:

Definition 1. An interval-valued spherical fuzzy set $\tilde{A}_S$ of the universe of discourse U is defined as

$$\tilde{A}_S = \left\{ u, \left[\mu^L_{\tilde{A}_S}(u), \mu^U_{\tilde{A}_S}(u) \right], \left[v^L_{\tilde{A}_S}(u), v^U_{\tilde{A}_S}(u) \right], \left[\pi^L_{\tilde{A}_S}(u), \pi^U_{\tilde{A}_S}(u) \right] | u \in U \right\} \tag{10}$$

where $0 \le \mu^L_{\tilde{A}_S}(u) \le \mu^U_{\tilde{A}_S}(u) \le 1$; $0 \le v^L_{\tilde{A}_S} \le v^U_{\tilde{A}_S}(u) \le 1$ and $0 \le \mu^L_{\tilde{A}_S}(u) \le \mu^U_{\tilde{A}_S}(u) \le 1$

and $0 \le (\mu^U_{\tilde{A}_S}(u))^2 + (v^U_{\tilde{A}_S}(u))^2 + (\mu^U_{\tilde{A}_S}(u))^2 \le 1$. For each $u \in U, \mu^U_{\tilde{A}_S}(u), v^U_{\tilde{A}_S}(u)$ and $\mu^U_{\tilde{A}_S}(u)$ are the upper degrees of membership, non-membership, and hesitancy degrees of u to $\tilde{A}_S$. For each, $u \in U$, if $\mu^L_{\tilde{A}_S} = \mu^U_{\tilde{A}_S},(u), v^L_{\tilde{A}_S}(u) = v^U_{\tilde{A}_S}(u)$ and $\mu^L_{\tilde{A}_S}(u) = \mu^U_{\tilde{A}_S}(u)$ then an interval-valued spherical fuzzy set reduces to a single-valued spherical fuzzy set. For an interval-valued spherical fuzzy set, the pair $\left\langle \left[\mu^L_{\tilde{A}_S}(u), \mu^U_{\tilde{A}_S}(u) \right], \left[v^L_{\tilde{A}_S}(u), v^U_{\tilde{A}_S}(u) \right], \left[\mu^L_{\tilde{A}_S}(u), \mu^U_{\tilde{A}_S}(u) \right] \right\rangle$ is called an interval-valued spherical fuzzy number. For convenience, the pair $\left\langle \left[\mu^L_{\tilde{A}_S}(u), \mu^U_{\tilde{A}_S}(u) \right], \left[v^L_{\tilde{A}_S}(u), v^U_{\tilde{A}_S}(u) \right], \left[\mu^L_{\tilde{A}_S}(u), \mu^U_{\tilde{A}_S}(u) \right] \right\rangle$ is denoted by $\tilde{\alpha} = \langle [a,b],[c,d],[e,f] \rangle$ where $[a,b] \subset [0,1],[c,d] \subset [0,1],[e,f] \subset [0,1]; b^2 + d^2 + f^2 \le 1$.

Note that, $\tilde{\alpha}^+ = \langle [1,1],[0,0],[0,0] \rangle$; $\tilde{\alpha}^- = \langle [0,0],[1,1],[0,0] \rangle$ and $\tilde{\alpha}^* = \langle [0,0],[0,0],[1,1] \rangle$ are the largest, smallest and moderate interval-valued spherical fuzzy numbers, respectively.

Definition 2. Basic operations of interval-valued spherical fuzzy sets are given below:

Addition;

$$\tilde{\alpha}_1 \oplus \tilde{\alpha}_2 = \left\{ \begin{array}{l} \left[\left((a_1)^2 + (a_2)^2 - (a_1)^2 (a_2)^2 \right)^{1/2}, \left((b_1)^2 + (b_2)^2 - (b_1)^2 (b_2)^2 \right)^{1/2} \right], \\ \left[c_1 c_2, d_1 d_2 \right] \\ \left[\begin{array}{l} \left(1 - (a_2)^2 (e_1)^2 + ((1 - (a_1)^2 (e_2)^2 - (e_1^2)(e_2)^2 \right)^{1/2}, \\ \left(\left(1 - (b_2)^2 (f_1)^2 + ((1 - (b_1)^2 (f_2^2) - (f_1^2)(f_2)^2 \right)^{1/2} \right) \end{array} \right] \end{array} \right\} \tag{11}$$

Multiplication;

$$\tilde{\alpha}_1 \otimes \tilde{\alpha}_2 = \left\{ \begin{array}{l} [a_1 a_2, b_1 b_2], \left[\left((c_1)^2 + (c_2)^2 - (c_1)^2 (c_2)^2 \right)^{1/2}, \left((d_1)^2 + (d_2)^2 - (d_1)^2 (d_2)^2 \right)^{1/2} \right], \\ \left[\begin{array}{l} \left(1 - (c_2)^2 (e_1)^2 + ((1 - (c_1)^2 (e_2^2) - (e_1^2)(e_2^2) \right)^{1/2}, \\ \left(\left(1 - (d_2)^2 (f_1)^2 + ((1 - (d_1)^2 (f_2^2) - (f_1^2)(f_2^2) \right)^{1/2} \right) \end{array} \right] \end{array} \right\} \tag{12}$$

Multiplication by a scalar λ; $\lambda > 0$

$$\lambda.\tilde{\alpha} = \left\{ \begin{array}{l} \left[\left(1 - \left(1 - a^2 \right)^{\lambda} \right)^{1/2}, \left(1 - \left(1 - b^2 \right)^{\lambda} \right)^{1/2} \right], \left[c^{\lambda}, d^{\lambda} \right], \\ \left[\left(\left(1 - a^2 \right)^{\lambda} - \left(1 - a^2 - e^2 \right)^{\lambda} \right)^{1/2}, \left(\left(1 - b^2 \right)^{\lambda} - \left(1 - b^2 - f^2 \right)^{\lambda} \right)^{1/2} \right] \end{array} \right\} \tag{13}$$

λ th power $\tilde{\alpha}$; $\lambda > 0$

$$\tilde{\alpha}^{\lambda} = \left\{ \begin{array}{l} [a^{\lambda}, b^{\lambda}], \left[\left(1-\left(1-c^2\right)^{\lambda}\right)^{1/2}, \left(1-\left(1-d^2\right)^{\lambda}\right)^{1/2} \right], \\ \left[\left(\left(1-c^2\right)^{\lambda} - \left(1-c^2-e^2\right)^{\lambda}\right)^{1/2}, \left(\left(1-d^2\right)^{\lambda} - \left(1-d^2-f^2\right)^{\lambda}\right)^{1/2} \right] \end{array} \right\} \tag{14}$$

Definition 3. Interval-valued spherical fuzzy weighted geometric mean $IVSFWGM$ operator is defined as follows:

$$IVSFWGM_w(\tilde{\alpha}_1, \tilde{\alpha}_2, \ldots, \tilde{\alpha}_n) = \tilde{\alpha}_1^{w_1} \otimes \tilde{\alpha}_2^{w_2} \otimes \ldots \otimes \tilde{\alpha}_n^{w_n} =$$

$$\left\{ \begin{array}{l} \left[\prod_{j=1}^{n} a_j^{w_j}, \prod_{j=1}^{n} b_j^{w_j} \right], \left[\left(1-\prod_{i=1}^{n}\left(1-c_j^2\right)^{w_j}\right)^{1/2}, \left(1-\prod_{i=1}^{n}\left(1-d_j^2\right)^{w_j}\right)^{1/2} \right], \\ \left[\left(1-\prod_{i=1}^{n}\left(1-c_j^2\right)^{w_j} - \prod_{i=1}^{n}\left(1-c_j^2-e_j^2\right)^{w_j}\right)^{1/2}, \left(1-\prod_{i=1}^{n}\left(1-d_j^2\right)^{w_j} - \prod_{i=1}^{n}\left(1-d_j^2-f_j^2\right)^{w_j}\right)^{1/2} \right] \end{array} \right\} \tag{15}$$

Definition 4. Score and accuracy functions are defined as follows:

$$Score(\tilde{\alpha}) = \frac{a^2+b^2-c^2-d^2-(e/2)^2-(f/2)^2}{2} \tag{16}$$

$$Accuracy(\tilde{\alpha}) = \frac{a^2+b^2+c^2+d^2+e^2+f^2}{2} \tag{17}$$

2.3. Proposed Methodology: Interval-Valued Spherical Fuzzy ARAS

The flowchart (Figure 1) and steps of the proposed model are as follows:

Define an MCDM problem with feasible criteria and alternatives

Step 1: Linguistic evaluations of alternatives with respect to criteria

Step 2: Interval-valued spherical fuzzy alternative evaluation matrix

Step 3: Criterion importance level assignments in a linguistic manner

Step 4: Interval-valued spherical fuzzy criterion weight matrix

Step 5: Interval-valued spherical fuzzy decsion matrix

Step 6: Ideal solution based on score and accuracy functions

Step 7: Interval-valued spherical fuzzy optimality function values

Step 8: Defuzzified optimality function values

Step 9: Utility degrees of alternatives and final ranking

Sensitivity and comparative analysis

Figure 1. The flowchart of the proposed model: Interval-valued spherical fuzzy ARAS.

Define an MCDM problem with a set of alternatives and the most related criteria. Let $A_i = (A_1, A_2, \ldots, A_m)$ be the alternatives and $C_j = (A_1, A_2, \ldots, A_n)$ be the selected criteria set.

Step 1. The selected alternatives are evaluated by decision-makers with respect to criteria by utilizing the linguistic terms that is given in Table 1.

In Table 1, μ^L, ν^L and π^L are the lower, and μ^U, ν^U and π^U are the upper degrees of membership, non-membership, and hesitancy degrees.

Step 2. Linguistic evaluations of each decision-maker are transformed to interval-valued spherical fuzzy numbers in a matrix form. The linguistic scale that is given in Table 1 is used for the conversion operation. Then, all matrices are aggregated to obtain one unique collective matrix, which is called the interval-valued spherical fuzzy alternative evaluation matrix.

Table 1. Linguistic terms and corresponding interval-valued spherical fuzzy numbers.

Linguistic term	μ^L, μ^U	v^L, v^U	π^L, π^U
Absolutely most important (AMI)	[0.85, 0.95]	[0.10, 0.15]	[0.05, 0.15]
Very high importance (VHI)	[0.75, 0.85]	[0.15, 0.20]	[0.15, 0.20]
High importance (HI)	[0.65, 0.75]	[0.20, 0.25]	[0.20, 0.25]
Slightly more importance (SMI)	[0.55, 0.65]	[0.25, 0.30]	[0.25, 0.30]
Equal importance (EI)	[0.50, 0.55]	[0.45, 0.55]	[0.30, 0.40]
Slightly low importance (SLI)	[0.25, 0.30]	[0.55, 0.65]	[0.25, 0.30]
Low importance (LI)	[0.20, 0.25]	[0.65, 0.75]	[0.20, 0.25]
Very low importance (VLI)	[0.15, 0.20]	[0.75, 0.85]	[0.15, 0.20]
Absolutely least important (ALI)	[0.10, 0.15]	[0.85, 0.95]	[0.05, 0.15]

Step 3. Decision-makers evaluate the importance level of each criterion by utilizing the same linguistic terms that is given in Table 1.

Step 4. Linguistic criterion evaluations are converted to interval-valued spherical fuzzy numbers and aggregated to obtain one unique matrix which is called interval-valued spherical fuzzy criterion weight matrix.

Step 5. Interval-valued spherical fuzzy decision matrix *D* is obtained by multiplying the alternative evaluation matrix (*Step 2*) by criterion weights (*Step 3*). Equation 3 is used for the multiplication operation. The structure of the decision matrix is given in equation 18.

$$\widetilde{D} = C_J(A_i)_{\mathrm{mxn}} = \begin{bmatrix} \tilde{r}_{11} & \tilde{r}_{12} & \cdots & \tilde{r}_{1n} \\ \tilde{r}_{21} & \tilde{r}_{22} & \cdots & \tilde{r}_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ \tilde{r}_{m1} & \tilde{r}_{m2} & \cdots & \tilde{r}_{mn} \end{bmatrix} \tag{18}$$

where $\tilde{r}_{ij} = \mu_{ij}, \nu_{ij}, \pi_{ij}$ is the interval-valued spherical fuzzy element of the evaluation matrix; the evaluation of alternative A_i ($i = 1, 2, \ldots, m$) with respect to criterion C_j ($j = 1, 2, \ldots, n$) is donated by $\widetilde{D} = C_j(A_i)_{mxn}$ is an interval-valued spherical fuzzy decision matrix, and μ_{ij}, ν_{ij} and π_{ij} are the membership, non-membership and hesitancy degrees for the *i*th alternative and *j*th criterion.

Step 6. Determine the interval-valued spherical fuzzy ideal solution based on score and accuracy values of attributes in decision matrix $\widetilde{D}$. Equations 7 and 8 are used to calculate score and accuracy values.

Step 7. Determine the interval-valued spherical fuzzy optimality function values O_i for all alternatives, as well as for the interval-valued spherical fuzzy ideal best solution O_o as given in equations 19 and 20.

$$\tilde{O}_i = [a_{i1}, \mathrm{b}_{i1}][\mathrm{c}_{i1}, \mathrm{d}_{i1}], [\mathrm{e}_{i1}, \mathrm{f}_{i1}] + [a_{i2}, \mathrm{b}_{i2}][\mathrm{c}_{i2}, \mathrm{d}_{i2}][\mathrm{e}_{i2}, \mathrm{f}_{i2}] + \cdots + [a_{in}, \mathrm{b}_{in}][\mathrm{c}_{in}, \mathrm{d}_{in}][\mathrm{e}_{in}, \mathrm{f}_{in}] \tag{19}$$

where $\tilde{O}_i$ gives the optimality function value for the *i*th alternative and *n* is the number of criteria. Thus, $[a_{i1}, \mathrm{b}_{i1}], [\mathrm{c}_{i1}, \mathrm{d}_{i1}], [\mathrm{e}_{i1}, \mathrm{f}_{i1}]$ are the lower and upper degrees of membership, non-membership and hesitancy for the first criterion of the *i*th alternative and so on.

$$\tilde{O}_o = [a_{o1}, \mathrm{b}_{o1}][\mathrm{c}_{o1}, \mathrm{d}_{o1}], [\mathrm{e}_{o1}, \mathrm{f}_{o1}] + [a_{o2}, \mathrm{b}_{o2}][\mathrm{c}_{o2}, \mathrm{d}_{o2}][\mathrm{e}_{o2}, \mathrm{f}_{o2}] + \cdots + [a_{on}, \mathrm{b}_{on}][\mathrm{c}_{on}, \mathrm{d}_{on}][\mathrm{e}_{on}, \mathrm{f}_{on}] \tag{20}$$

where $\tilde{O}_o$ gives the optimality function value for the ideal best solution and n is the number of criteria. Addition operator that is given in equation 2 is used for calculating $\tilde{O}_i$ and $\tilde{O}_o$.

Step 8. Defuzzify and obtain crisp form of $\tilde{O}_i$ and $\tilde{O}_o$. Then calculate the utility degree K_i of an alternative A_i by comparing optimality criterion value of that alternative O_i with the optimality criterion value of the ideal best solution O_o as given in equation 21.

$$K_i = \frac{O_i}{O_o} \tag{21}$$

Step 9. Rank the alternatives according to utility degrees K_i of the alternatives. The higher the utility value, the better the alternative.

3. Application

In this section, the applicability of the interval-valued spherical fuzzy ARAS model is shown to evaluate seismic risk levels of hospital buildings. In this regard, four hospital buildings (A1, A2, A3, and A4) are evaluated by three civil engineer decision-makers with respect to eight selected criteria. The structure of the MCDM problem (Figure 2) and a brief summary of the selected criteria are given below.

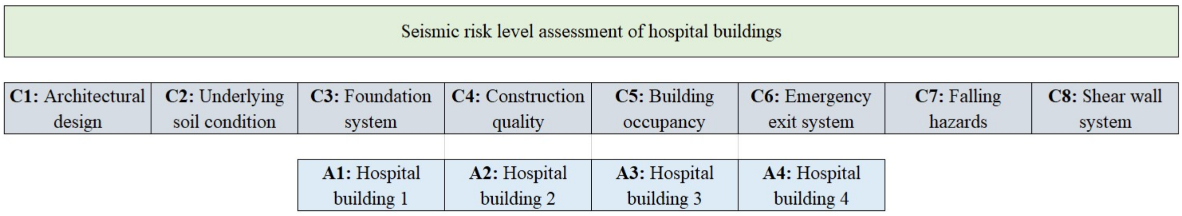

Figure 2. The structure of the MCDM problem.

3.1. Criteria Set

Previous earthquake events have shown that there is a need for the harmony of structural and non-structural elements for the seismic performance of buildings [26]. On the other hand, in seismic risk analysis studies, assessments of critical public institutions such as hospitals in terms of non-structural factors are very critical [27]. In this study, based on comprehensive literature analysis, five structural (C1, C2, C3, C4, and C8); and three non-structural criteria (C5, C6, and C7) were determined for the seismic risk analysis study as follows:

C1 Architectural design. Architectural design of buildings plays an important role in structural performance and may lead to complex behaviors under earthquake loadings [28].

C2 Underlying soil condition. Underlying soil condition significantly affects structural performances of buildings and should be considered in seismic vulnerability assessments [29].

C3 Foundation system. Foundation system is also an important part of a structure which transmits vertical loadings to the soil and may be responsible for failure under seismicity [30].

C4 Construction quality. Construction material quality is a critical criterion when evaluating seismic vulnerability and it may lead to severe damages after an earthquake if its quality is not high enough [31].

C5 Building occupancy. Building occupancy is another criterion in determining the seismic vulnerability level of the buildings and can be determined by qualitative assessments of experts [32].

C6 Emergency exit system. Emergency exit systems in these buildings are critical for exit and access after an earthquake [33].

C7 Falling hazards. Falling hazards such as external falling hazards, i.e., unreinforced masonry parapets, chimneys and exterior surface cladding elements; and internal falling hazards, i.e., chemicals in laboratories can fall or block exit ways under earthquake [34].

C8 Shear wall system. Shear wall system also has an important role in the design of buildings against seismic hazards since these walls make structures more resistant against lateral loads by providing efficient bracing system [35].

3.2. Numerical Solution: Interval-Valued Spherical Fuzzy ARAS Set

Step 1. Four hospital buildings are evaluated with respect to eight criteria by three civil engineer experts having same experience levels. Thus, each decision-maker has an equal weight as 1/3. Linguistic evaluations of alternatives are given in Table 2.

Table 2. Linguistic evaluations of alternatives.

		C1	C2	C3	C4	C5	C6	C7	C8
DM1	A1	EI	SMI	SMI	SMI	VHI	EI	EI	EI
	A2	SMI	VLI	VHI	HI	VHI	HI	LI	VHI
	A3	VLI	VHI	SMI	HI	VHI	HI	VLI	SLI
	A4	SLI	SMI	SLI	SMI	EI	EI	ALI	SLI
DM2	A1	SMI	VHI	SMI	VHI	VHI	EI	EI	SLI
	A2	SMI	SLI	VHI	HI	HI	VHI	SLI	VHI
	A3	SLI	HI	HI	VHI	HI	SMI	ALI	EI
	A4	SLI	SLI	SMI	SMI	SMI	EI	ALI	EI
DM3	A1	EI	SMI	HI	SMI	AMI	LI	SLI	SLI
	A2	VHI	LI	VHI	HI	HI	SLI	LI	HI
	A3	EI	SMI	SMI	AMI	SLI	LI	LI	SLI
	A4	VLI	SMI	SLI	EI	SLI	LI	VLI	EI

*Step 2***.** Interval-valued spherical fuzzy alternative evaluation matrix is constructed as in Table 3.

Table 3. Interval-valued spherical fuzzy alternative evaluation matrix.

	C1	C2	…	C8
A1	([0.52, 0.58], [0.40, 0.49], [0.29, 0.38])	([0.55, 0.65], [0.25, 0.30], [0.25, 0.30])	…	([0.31, 0.37], [0.52, 0.62], [0.27, 0.33])
A2	([0.61, 0.71], [0.22, 0.27], [0.22, 0.27])	([0.20, 0.25], [0.66, 0.77], [0.20, 0.25])	…	([0.72, 0.82], [0.17, 0.22], [0.17, 0.22])
A3	([0.27, 0.32], [0.61, 0.72], [0.23, 0.29])	([0.64, 0.75], [0.20, 0.25], [0.21, 0.25])	…	([0.31, 0.37], [0.52, 0.62], [0.27, 0.33])
A4	([0.21, 0.26], [0.63, 0.74], [0.21, 0.26])	([0.42, 0.50], [0.39, 0.47], [0.25, 0.30])	…	([0.40, 0.45], [0.49, 0.59], [0.28, 0.37])

Steps 3 and 4. Linguistic evaluations of eight criteria by three decision-makers and corresponding interval-valued spherical fuzzy criterion weight matrix are given in Table 4.

Step 5. Interval-valued spherical fuzzy decision matrix is obtained as in Table 5.

Table 4. Linguistic evaluations of criteria and corresponding criterion weights.

	C1	C2	…	C8
DM1	HI	AMI	…	HI
DM2	HI	VHI	…	VHI
DM3	SMI	AMI	…	SMI
Criterion weights	([0.61, 0.72], [0.22, 0.27], [0.22, 0.27])	([0.82, 0.92], [0.12, 0.17], [0.10, 0.17])	…	([0.64, 0.75], [0.20, 0.25], [0.21, 0.25])

Table 5. Decision matrix.

	C1	C2	…	C8
A1	([0.32, 0.42], [0.45, 0.54], [0.34, 0.42])	([0.45, 0.60], [0.28, 0.34], [0.26, 0.33])	…	([0.20, 0.27], [0.55, 0.65], [0.31, 0.37])
A2	([0.37, 0.51], [0.31, 0.37], [0.30, 0.36])	([0.16, 0.23], [0.67, 0.77], [0.21, 0.26])	…	([0.46, 0.61], [0.26, 0.33], [0.26, 0.32])
A3	([0.16, 0.23], [0.64, 0.74], [0.28, 0.33])	([0.53, 0.68], [0.24, 0.30], [0.22, 0.30])	…	([0.20, 0.27], [0.55, 0.65], [0.31, 0.37])
A4	([0.13, 0.19], [0.66, 0.76], [0.26, 0.30])	([0.34, 0.46], [0.40, 0.49], [0.26, 0.33])	…	([0.26, 0.34], [0.52, 0.62], [0.32, 0.40])

Steps 6-9. Optimality criterion values for the alternatives and for the ideal best solution, and appraisal scores of alternatives are obtained as in Table 6.

Table 6. Optimality criterion values, appraisal scores and final rankings of alternatives.

	Optimality criterion value	Appraisal score
A1	([0.77, 0.91], [0.00, 0.01], [0.46, 0.36])	0.772
A2	([0.84, 0.95], [0.00, 0.00], [0.36, 0.25])	0.906
A3	([0.81, 0.93], [0.00, 0.01], [0.39, 0.29])	0.841
A4	([0.62, 0.77], [0.01, 0.04], [0.54, 0.51])	0.487
Ideal best	([0.90, 0.98], [0.00, 0.00], [0.30, 0.17])	Final ranking A2 > A3 > A1 > A4

A2 has the highest degree of utility which means seismic risk level of hospital building A2 is the most critical.

3.3. Sensitivity, Comparative and Rank Reversal Analyses

Sensitivity analysis. To validate our model, sensitivity, comparative, and rank reversal analyses were conducted. For sensitivity analysis of criteria, one-at-a-time analysis was conducted with respect to each criterion, and for this purpose, reference criterion weight values, namely absolutely most important (AMI), equal importance (EI) and absolutely least important (ALI) were defined to see the effect of the change of criterion weights on the final rankings. By assigning each reference value to each criterion, the proposed model was executed and the scores and the final rankings were calculated. 24 scenarios obtained in this way are given in Figure 3.

The ranks of A4 and A1 are the same in all scenarios, whereas the rankings of A3 and A2 vary in four of the 24 scenarios. In general, however, the suggested technique produced rather consistent results for a variety of criteria weight situations.

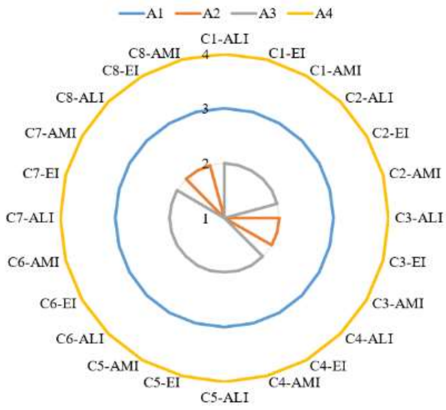

Figure 3. Sensitivity analysis results for criterion weights.

The second analysis was conducted to check the effect of decision-maker weights on the final rankings. In this context, 10 different scenarios were generated, provided that the sum of the weights of three decision-makers is one. The proposed model was executed for these 10 scenarios by assigning extreme values to the decision-maker weights as much as possible. The ranking of alternatives obtained in this way is shown in Figure 4.

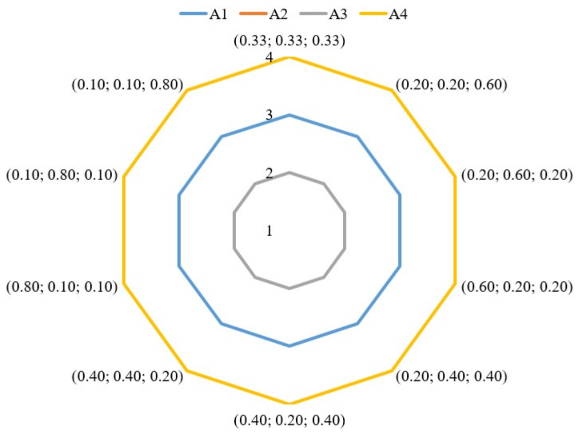

Figure 4. Sensitivity analysis results for decision-maker weights.

In all scenarios, the alternative ranks are the same. It can be said that, the proposed methodology has a robust behavior under different extreme decision-maker weight distribution cases.

Comparative analysis. For comparing the validity of our method, we compared the appraisal scores of the proposed method with single-valued spherical fuzzy ARAS [36].

Both techniques provided the same outcomes in terms of ranking. It can be said that the proposed interval-valued spherical fuzzy ARAS gives highly correlated results with single-valued approach.

Rank reversal analysis. When one of the alternatives is eliminated or a new alternative is introduced to an MCDM model, the ranking result of the model may change, which is known as a rank reversal phenomenon. Rank reversal may occur in commonly used MCDM techniques, which can degrade the dependability of the applied method by causing the model to provide inaccurate findings. In this work, the rank reversal capacity of the suggested interval-valued spherical fuzzy ARAS was also investigated.

Table 9. Comparative analysis results.

	Proposed interval-valued spherical fuzzy ARAS	Single-valued spherical fuzzy ARAS
A1	0.772	0.680
A2	0.906	0.876
A3	0.841	0.786
A4	0.487	0.453
Ranking	*A2 > A3 > A1 > A4*	*A2 > A3 > A1 > A4*

Each alternative was successively eliminated from the full model, and the appraisal scores were computed by executing the algorithm. By deleting the alternatives, a total of eight scenarios were obtained. In the first scenario, alternative A1 was deleted from the whole model, and the appraisal scores and final rankings of other alternatives were obtained. Alternatives A2, A3, and A4 were deleted one by one in the second, third, and fourth scenarios.

In the same way, only alternatives A1 and A2 were evaluated in the fifth scenario; alternatives A3 and A4 were evaluated in the sixth scenario; alternatives A1 and A4 were evaluated in the seventh scenario, and alternatives A2 and A3 were evaluated in the eighth scenario. Table 10 shows the appraisal scores and final rankings that were obtained in this manner.

Table 10. Rank reversal analysis results.

Scenario	A1	A2	A3	A4	Ranking
Full Model	0.680	0.876	0.786	0.453	*A2 > A3 > A1 > A4*
1	-	0.877	0.787	0.453	*A2 > A3 > A4*
2	0.831	-	0.962	0.554	*A3 > A1 > A4*
3	0.725	0.935	-	0.483	*A2 > A1 > A4*
4	0.680	0.876	0.786	-	*A2 > A3 > A1*
5	0.725	0.935	-		*A2 > A1*
6	-	-	0.995	0.573	*A3 > A4*
7	0.992	-	-	0.661	*A1 > A4*
8	-	0.877	0.787	-	*A2 > A3*

4. Conclusion and Future Remarks

In this study, a new decision support model is established by integrating ARAS methodology with interval-valued spherical fuzzy sets. The applicability of the model is illustrated by assessing the seismic risk levels of hospital structures. For this aim, three civil engineer decision-maker experts evaluated four hospital structures based on eight criteria derived from the literature. Mathematical operations of interval-valued spherical fuzzy sets were used in the model development. Comparative, sensitivity, and rank reversal analyses are given to demonstrate the stability and validity of the proposed model.

The main theoretical contributions of this study are as follows: the ARAS method is extended with interval-valued spherical fuzzy sets which provide users an increased fuzziness modeling capacity. The interval-valued spherical fuzzy addition operation was used to construct optimality criterion values. Sensitivity analysis for criterion and decision-maker weights distribution scenarios are provided.

This study has also some practical implications: A fuzzy decision-making framework is provided for site-specific seismic risk assessment of hospital buildings. The suggested model can be utilized by hospital administrators to analyze the seismic risk levels of hospital structures quickly and cost-effectively for use in retrofitting and rebuilding planning.

As a limitation of the study, the following can be said: In the model development, degree of alternative utility was calculated by comparing optimality criterion value of an alternative with the optimality criterion value of the ideal best solution. However, in this final step, the model was converted to a crisp environment due to the absence of spherical fuzzy division operator.

The addition operator was used to calculate the spherical fuzzy optimality function in this work. In the future, geometric and arithmetic mean operators might be utilized to do this. For seismic risk assessment, a machine learning reinforced MCDM model may also be created.

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References

[1] Cimellaro, G. P., Reinhorn, A. M., & Bruneau, M. (2010). Seismic resilience of a hospital system. Structure and Infrastructure Engineering, 6(1-2), 127-144. DOI: https://doi.org/10.1080/15732470802663847.

[2] Perrone, D., Aiello, M. A., Pecce, M., & Rossi, F. (2015, August). Rapid visual screening for seismic evaluation of RC hospital buildings. In Structures (Vol. 3, pp. 57-70). Elsevier. DOI: https://doi.org/10.1016/j.istruc.2015.03.002.

[3] Delavar, M. R., & Sadrykia, M. (2020). Assessment of enhanced Dempster-Shafer theory for uncertainty modeling in a GIS-based seismic vulnerability assessment model, case study Tabriz city. ISPRS International Journal of Geo-Information, 9(4), 195. DOI: https://doi.org/10.3390/ijgi9040195.

[4] Kutlu Gündoğdu, F., & Kahraman, C. (2019a). Spherical fuzzy sets and spherical fuzzy TOPSIS method. Journal of intelligent & fuzzy systems, 36(1), 337-352. DOI: https://doi.org/10.3233/JIFS-181401.

[5] Kutlu Gündoğdu, F., & Kahraman, C. (2019b). A novel fuzzy TOPSIS method using emerging interval-valued spherical fuzzy sets. Engineering Applications of Artificial Intelligence, 85, 307-323. DOI: https://doi.org/10.1016/j.engappai.2019.06.003.

[6] Zavadskas, E. K., & Turskis, Z. (2010). A new additive ratio assessment (ARAS) method in multicriteria decision-making. Technological and Economic Development of Economy, 16(2), 159-172. DOI: https://doi.org/10.3846/tede.2010.10.

[7] Karagöz, S., Deveci, M., Simic, V., & Aydin, N. (2021). Interval type-2 Fuzzy ARAS method for recycling facility location problems. Applied Soft Computing, 102, 107107. DOI: https://doi.org/10.1016/j.asoc.2021.107107.

[8] Jaukovic Jocic, K.; Jocic, G.; Karabasevic, D.; Popovic, G.; Stanujkic, D.; Zavadskas, E.K.; Thanh Nguyen, P. A Novel Integrated PIPRECIA–Interval-Valued Triangular Fuzzy ARAS Model: E-Learning Course Selection. Symmetry 2020, 12, 928. DOI: https://doi.org/10.3390/sym12060928.

[9] Heidary Dahooie, J., Estiri, M., Zavadskas, E. K., & Xu, Z. (2021). A Novel Hybrid Fuzzy DEA-Fuzzy ARAS Method for Prioritizing High-Performance Innovation-Oriented Human Resource Practices in High Tech SME's. International Journal of Fuzzy Systems, 1-26. DOI: https://doi.org/10.1007/s40815-021-01162-2.

[10] Büyüközkan, G., & Güler, M. (2020). Smart watch evaluation with integrated hesitant fuzzy linguistic SAW-ARAS technique. Measurement, 153, 107353. DOI: https://doi.org/10.1016/j.measurement.2019.107353.

[11] Yildirim, B. F., & Mercangoz, B. A. (2020). Evaluating the logistics performance of OECD countries by using fuzzy AHP and ARAS-G. Eurasian Economic Review, 10(1), 27-45. DOI: https://doi.org/10.1007/s40822-019-00131-3.

[12] Gul, S. (2021). Fermatean fuzzy set extensions of SAW, ARAS, and VIKOR with applications in COVID-19 testing laboratory selection problem. Expert Systems, e12769. DOI: https://doi.org/10.1111/exsy.12769.

[13] Gul, M., & Ak, M. F. (2021). A modified failure modes and effects analysis using interval-valued spherical fuzzy extension of TOPSIS method: case study in a marble manufacturing facility. Soft Computing, 25(8), 6157-6178. DOI: https://doi.org/10.1007/s00500-021-05605-8.

[14] Aydin & Gundogdu F. K. (2021) Interval-Valued Spherical Fuzzy MULTIMOORA Method and Its Application to Industry 4.0. In *Decision Making with Spherical Fuzzy Sets* (pp. 295-322). Springer, Cham. DOI: https://doi.org/10.1007/978-3-030-45461-6 13.

[15] Duleba, S., Kutlu Gündoğdu, F., & Moslem, S. (2021). Interval-Valued Spherical Fuzzy Analytic Hierarchy Process Method to Evaluate Public Transportation Development. Informatica, 1-26. DOI: https://doi.org/10.15388/21-INFOR451.

[16] Jin, C., Ran, Y., Wang, Z., & Zhang, G. (2021). Prioritization of key quality characteristics with the three-dimensional HoQ model-based interval-valued spherical fuzzy-ORESTE method. Engineering Applications of Artificial Intelligence, 104, 104271. DOI: https://doi.org/10.1016/j.engappai.2021.104271.

[17] Lathamaheswari, M., Nagarajan, D., Garg, H., & Kavikumar, J. (2021). Interval Valued Spherical Fuzzy Aggregation Operators and Their Application in Decision Making Problem. In Decision Making with Spherical Fuzzy Sets (pp. 27-51). Springer, Cham. DOI: https://doi.org/10.1007/978-3-030-45461-6 2.

[18] Ozceylan, E., Ozkan, B., Kabak, M., & Dagdeviren, M. (2020, July). A Survey on spherical fuzzy sets and clustering the literature. In International Conference on Intelligent and Fuzzy Systems (pp. 87-97). Springer, Cham. DOI: https://doi.org/10.1007/978-3-030-51156-2 12.

[19] Adafer, S., & Bensaibi, M. (2017). Seismic vulnerability classification of roads. Energy Procedia, 139, 624-630. DOI: https://doi.org/10.1016/j.egypro.2017.11.263.

[20] Jena, R., Pradhan, B., & Beydoun, G. (2020). Earthquake vulnerability assessment in Northern Sumatra province by using a multi-criteria decision-making model. International journal of disaster risk reduction, 46, 101518. DOI: https://doi.org/10.1016/j.ijdrr.2020.101518.

[21] Kumlu, K. B. Y., & Tüdeş, Ş. (2019). Determination of earthquake-risky areas in Yalova City Center (Marmara region, Turkey) using GIS-based multicriteria decision-making techniques (analytical hierarchy process and technique for order preference by similarity to ideal solution). Natural Hazards, 96(3), 999-1018. DOI: https://doi.org/10.1007/s11069-019-03583-7.

[22] Cremen, G., & Galasso, C. (2021). A decision-making methodology for risk-informed earthquake early warning. Computer-Aided Civil and Infrastructure Engineering, 36(6), 747-761. DOI: https://doi.org/10.1111/mice.12670.

[23] Alizadeh, M., Hashim, M., Alizadeh, E., Shahabi, H., Karami, M. R., Beiranvand Pour, A. & Zabihi, H. (2018). Multi-criteria decision making (MCDM) model for seismic vulnerability assessment (SVA) of urban residential buildings. ISPRS International Journal of Geo-Information, 7(11), 444. DOI: https://doi.org/10.3390/ijgi7110444.

[24] Tyagi, A., Tiwari, R. K., & James, N. (2021). GIS-Based Landslide Hazard Zonation and Risk Studies Using MCDM. In Local Site Effects and Ground Failures (pp. 251-266). Springer, Singapore. DOI: https://doi.org/10.1007/978-981-15-9984-2 22.

[25] Zhang, F., Li, S., Wang, J., & Zhang, J. (2020). Effects of fault rupture on seismic responses of fault-crossing simply-supported highway bridges. Engineering Structures, 206, 110104. DOI: https://doi.org/10.1016/j.engstruct.2019.110104.

[26] Gabbianelli, G., Perrone, D., Brunesi, E., & Monteiro, R. (2020). Seismic acceleration and displacement demand profiles of non-structural elements in hospital buildings. Buildings, 10(12), 243. DOI: https://doi.org/10.3390/buildings10120243.

[27] Dixit, A. M., Yatabe, R., Guragain, R., Dahal, R. K., & Bhandary, N. P. (2014). Non-structural earthquake vulnerability assessment of major hospital buildings in Nepal. Georisk: Assessment and Management of Risk for Engineered Systems and Geohazards, 8(1), 1-13. DOI: https://doi.org/10.1080/17499518.2013.805629.

[28] Alecci, V., & De Stefano, M. (2019). Building irregularity issues and architectural design in seismic areas. Frattura ed Integrità Strutturale, 13(47), 161-168. DOI: https://doi.org/10.1016/j.asoc.2020.106322.

[29] Behnamfar, F., & Banizadeh, M. (2016). Effects of soil–structure interaction on distribution of seismic vulnerability in RC structures. Soil Dynamics and Earthquake Engineering, 80, 73-86. DOI: https://doi.org/10.1016/j.soildyn.2015.10.007.

[30] Adewuyi O, I., & Philips O, F. (2019). Integrated Geophysical and Geotechnical Methods for Pre-Foundation Investigations. Journal of Geology & Geophysics, 08(01). DOI: https://doi.org/10.4172/2381-8719.1000453.

[31] Kaplan, H., Bilgin, H., Yilmaz, S., Binici, H., & Öztas, A. (2010). Structural damages of L'Aquila (Italy) earthquake. Natural Hazards and Earth System Sciences, 10(3), 499-507. DOI: https://doi.org/10.5194/nhess-10-499-2010.

[32] Ketsap, A., Hansapinyo, C., Kronprasert, N., & Limkatanyu, S. (2019). Uncertainty and fuzzy decisions in earthquake risk evaluation of buildings. Engineering Journal, 23(5), 89-105. DOI: https://doi.org/10.4186/ej.2019.23.5.89.

[33] Li, B., & Mosalam, K. M. (2013). Seismic performance of reinforced-concrete stairways during the 2008 Wenchuan earthquake. Journal of performance of constructed facilities, 27(6), 721-730. DOI: https://doi.org/10.1061/(ASCE)CF.1943-5509.0000382.

[34] De Angelis, A., & Pecce, M. (2015). Seismic nonstructural vulnerability assessment in school buildings. Natural Hazards, 79(2), 1333-1358.

[35] Chandurkar, P. P., & Pajgade, D. P. (2013). Seismic analysis of RCC building with and without shear wall. International journal of modern engineering research, 3(3), 1805-1810.

[36] Menekşe, A., & Camgöz Akdağ, H. (2021, August). Seismic Vulnerability Assessment Using Spherical Fuzzy ARAS. In International Conference on Intelligent and Fuzzy Systems (pp. 733-740). Springer, Cham. DOI: https://doi.org/10.1007/978-3-030-85577-2_86.