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A GIS-BASED MULTI-CRITERIA EVALUATION FRAMEWORK FOR UNCERTAINTY REDUCTION IN EARTHQUAKE DISASTER MANAGEMENT USING GRANULAR COMPUTING

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Abstract. One of the most important steps in earthquake disaster management is the prediction of probable damages which is called earthquake vulnerability assessment. Earthquake vulnerability assessment is a multi-criteria problem and a number of multi-criteria decision making models have been proposed for the problem. Two main sources of uncertainty including uncertainty associated with experts' point of views and the one associated with attribute values exist in the earthquake vulnerability assessment problem. If the uncertainty in these two sources is not handled properly the resulted seismic vulnerability map will be unreliable. The main objective of this research is to propose a reliable model for earthquake vulnerability assessment which is able to manage the uncertainty associated with the experts' opinions. Granular Computing (GrC) is able to extract a set of if-then rules with minimum incompatibility from an information table. An integration of Dempster-Shafer Theory (DST) and GrC is applied in the current research to minimize the entropy in experts' opinions. The accuracy of the model based on the integration of the DST and GrC is 83%, while the accuracy of the single-expert model is 62% which indicates the importance of uncertainty management in seismic vulnerability assessment problem. Due to limited accessibility to current data, only six criteria are used in this model. However, the model is able to take into account both qualitative and quantitative criteria.

Keywords: Multi-Criteria Decision Making, GIS, disaster management, granular computing, earthquake vulnerability assessment, Dempster-Shafer Theory.

Introduction

Although the prediction of the precise time and location of an earthquake is impossible with the current equipment, prediction of the loss and probable damages seems to be feasible (Delavar *et al.* 2015; Rajarathnam, Santhakumar 2015; Moradi *et al.* 2015b). A variety of factors affect the vulnerability of an urban area against earthquake including height and age of the buildings, the quality of materials, population density and distance to active faults (Huang *et al.* 2015; Debnath 2013; Asadzadeh *et al.* 2015). Therefore, frequent models based on the integration of Geospatial Information System (GIS) and multi criteria analysis have been proposed in order to evaluate the vulnerability of urban areas against earthquake (Debnath 2013; Rashed, Weeks 2003; Malczewski, Liu 2014; Kim, Chung 2016). GIS is applied in seismic vulnerability assessment models in order to manipulate, store, analyse and represent the geospatial data. Being one of the most important issues in decision making, uncertainty has always been in the focus of researchers (Griffith 2014; Malczewski, Liu 2014). Poor uncertainty management strategy leads to unreliable and incorrect results (Ai *et al.* 2015). Two main sources of uncertainty are included in earthquake vulnerability assessment models (Abrahamson, Bommer 2005). The uncertainty in input attribute values and the uncertainty in experts' point of views (Panahi *et al.* 2014). The main objective of this paper is to handle the latter.

Extensive research has been undertaken to handle the uncertainty involved in earthquake vulnerability assessment (Rezaie, Panahi 2015; Panahi *et al.* 2013; Tyagunov *et al.* 2014). Baker and Cornell (2008) evaluated the main sources of uncertainty involved in earthquake vulnerability assessment models. They found that although applying more than one expert's opinion improves the model, it may increase uncertainty due to incompatibility in different experts' opinions. Emmi and Horton (1995) applied Monte Carlo simulation method to evaluate the impact of uncertainty associated with the input attribute values in earthquake vulnerability assessment models. They concluded that there is a direct relation between the input errors and the square of the error in the results. Al-Momani and Harrald (2003) tried to find the degree to which the seismic loss estimation models are sensitive to contributing criteria. They applied a sensitivity analysis method in order to evaluate the stability of the model. Moradi *et al.* (2013) applied the sensitivity analysis in the ordered weighted averaging and found that there is a direct relation between the vulnerability degree and the sensitivity of the vulnerability degree. Moradi *et al.* (2014) proposed a Group MCDM model for earthquake vulnerability assessment problem. Their model is able to take the judgments from more than one expert and produce a more reliable vulnerability map.

Defining earthquake physical vulnerability as a multi-criteria decision making process depends on various parameters including building properties like construction material and number of floors, earthquake characteristics such as intensity, surface topography attributes like slope, and expert's judgments which are accompanied with uncertainty (Erden, Karaman 2012; Hashemi, Alesheikh 2012). In this paper, six affective factors for seismic vulnerability assessment of Tehran is considered based on previous researches (Hashemi, Alesheikh 2012; Moradi *et al.* 2015a; Martins *et al.* 2012) including slope, earthquake intensity in terms of MMI units, percentage of weak buildings less than 4 floors, percentage of buildings with 4 floors and more, percentage of buildings built before 1966, and percentage of buildings built between 1966 and 1988.Tehran, the capital of Iran, is selected as the study area which contains 3175 statistical units situated between 51° 23′ E and 51° 33′ E Longitude and 34° 46′ N and 35° 49′ N Latitude.

GrC, as a general theory of problem solving and information processing (Skowron, Stepaniuk 2001; Lin *et al.* 2013; Pedrycz 2014) is employed to extract rules with minimum entropy for classifying the seismic vulnerability of statistical units. Construction of multiple levels of detail (granularity) which could be in the form of groups, classes, or clusters of the universe are used in this problem solving model (Chakraborty *et al.* 2013; Zhang, Miao 2013). It can be regarded for learning classification rules by considering two basic issues including the concept formation (making granules) and concept relationships identification (Nguyen *et al.* 2001). The concept is definitely considered as a piece of thought that is composed of two parts named extension and intension in the GrC model (Nguyen *et al.* 2001). Extension consists of items carrying the same attributes that describe the concept. The intension contains the entire attributes that are acceptable for the entire items. Association and exception rules are extracted by GrC in which association rules are the ones that are extracted according to associations amongst the two concepts; while exception rules are beneficial rules which are not extractable according to association rules.

The seismic vulnerability degree of sample data which is used as input in GrC, is determined based on experts' judgments. In order to minimize the uncertainty related to experts' judgments, a variety of experts' ideas can be used to define the vulnerability degree of sample statistical units. These judgments are then integrated based on Dempster-Shafer Theory (Yager 1987). DST is an extension of Bayesian theory that is used for integrating data acquired from independent sources as well as dealing with incomplete data (Beynon *et al.* 2001).

The scheme of this research starts with an overview of Dempster-Shafer theory in which basic ideas of this theory and its rule of combination are discussed in Section 2. In Section 3, the GrC concepts are reviewed and the basic formulas for extracting association rules and exception rules are presented. The methodology of mining the association and exception rules method are explained in Sections 4 and 5. Section 6 presents the proposed model for the seismic vulnerability assessment. Finally, the discussion and conclusion are presented in Section 7.

1. Dempster-Shafer Theory

Dempster-Shafer Theory (DST) is a theory of uncertainty management (Harmanec, Klir 1994). An allocation of probability mass is assigned to sets or intervals in this theory. The significant properties of DST are the capability of combining multiple sources (evidences) and modelling their conflicts (Yager 1992). The principles of DST are outlined below:

If $Q = \{h_1, h_2..., h_n\}$ shows a finite set of hypotheses (frame of discernment), for any subset of Q such as x, a basic probability number (BPN) could be defined as m: 2Q → [0, 1] that has the following properties (Yager 1992):

$$0 \le m(x) \le 1, \quad (1)$$

$$m(\varnothing) = 0 \ (\varnothing \text{ is empty set}), \quad (2)$$

$$\sum_{x \in 2} m(x) = 1. \quad (3)$$

For any subset x of the frame of discernment Q, $m(x)$ is the exact belief in the proposition depicted by x ranging in value between zero and one (Eq (1)). According to Eq (2), BPN of empty set is zero, and Eq (3) shows that sum of BPNs of the subsets of the reference set is one.

DST also provides a function to combine the measures of evidence. This combining function, $m_1 \oplus m_2$: 2Q → [0, 1] is defined in Eq (4) (Beynon *et al.* 2001):

$$\left[m_1 m_2\right](y) = \begin{cases} 0 & y = \varnothing \\ \dfrac{\sum_{AB=y} m_1(A) m_2(B)}{1 - \sum_{AB=\varnothing} m_1(A) m_2(B)} & y \neq \varnothing \end{cases}. \quad (4)$$

After the combination, experts' points of views in sample areas are combined and each sample is given a unique vulnerability potential.

2. Granular computing model

The granular computing model focuses on a general theory and methodology for problem solving and information processing by constructing multiple levels of granularity (Skowron, Stepaniuk 2001; Pedrycz 2014). Basic elements in granular computing are subsets, classes and clusters of a universe named granules (Lin *et al.* 2013).

In the granular computing model, granulation is defined as a grouping of individual elements of the universe into classes based on available information in the form of an information table (Lin 2012). In this model a finite set of objects named the universe is described by a finite set of attributes and is presented by Eq (5) (Pedrycz *et al.* 2012):

$$S = (U, A_t, L, \{V_a \mid a \in A_t\}, \{I_a \mid a \in A_t\}), \quad (5)$$

where

U is a finite non-empty set of objects,

A_t is a finite non-empty set of attributes,

L is a language defined by using attributes in A_t,

V_a is a non-empty set of values of $a \in A_t$,

$I_a : U \to V_a$ is an information function mapping an object from U to exactly one possible value of attribute a in V_a.

Some of the GrC basic formulas which are employed in this research for characterizing granules and finding their relationship between granules are described in the following:

2.1. Generality

The generality of concept Φ defined in Eq (6), displays the relative size of constructive granule of the concept Φ (Hońko 2013). The larger granule will result in the greater Generality.

$$G(\Phi) = \frac{|m(\Phi)|}{|U|}, \quad (6)$$

where $|\ m(\Phi)|$ is the size of constructive granule of concept Φ and $|U|$ is the size of constructive granule of universe.

2.2. Absolute support

For two given concepts Φ and Ψ, the absolute support (AS) or confidence of Ψ, provided by Φ is defined by Eq (7) (Sheikhian *et al.* 2015):

$$AS(\Phi \to \Psi) = \frac{|m(\Phi \wedge \Psi)|}{|m(\Phi)|} = \frac{|m(\Phi \cap \Psi)|}{|m(\Phi)|}, \quad (7)$$

where $m(\Phi \wedge \Psi)$ is the size of the constructive granule of concepts Φ and Ψ . And $|\ m(\Phi)|$ is the size of the conructive granule of concept Φ. This quantity displays the conditional probability of a randomly selected object satisfying Ψ, also satisfies Φ. The quantity $0 \le AS\ (\Psi \mid \Phi\ ) \le 1$ is the degree to which Φ implies Ψ (Skowron, Stepaniuk 2001).

2.3. Coverage

The coverage of concept Φ provided by concept Ψ is defined by Eq (8) (Yao, Yao 2002):

$$CV(\Phi \to \Psi) = \frac{|m(\Phi \wedge \Psi)|}{|m(\Psi)|} = \frac{|m(\Phi \cap \Psi)|}{|m(\Psi)|}, \quad (8)$$

where $|m(\Phi \wedge \Psi)|$ is the size of constructive granule of concept Φ and Ψ, and $|\ m(\Psi)|$ is the size of constructive anule of concept Ψ. This quantity displays the conditional probability of a randomly selected object satisfying Φ, also satisfies Ψ and shows the coverage of Ψ upon Φ (Yao, Yao 2002).

2.4. Change of support

Change of support (CS) of concept Ψ provided by concept Φ is defined by Eq (9) (Lin 1998):

$$CS(\Psi \mid \Phi) = AS(\Psi \mid \Phi) - G(\Psi). \qquad (9)$$

In this formula, $G(\Psi)$ may be considered as a priori probability of Ψ and $AS(\Psi \mid \Phi)$ as a posterior probability of that (Lin 1998). The difference of these probabilities is defined as the change of support and varies from –1 to 1.

The positive value confirms that Φ causes Ψ and negative value means Φ does not cause Ψ.

2.4. Conditional entropy

By considering a family formulas of $\Psi = \{\Psi_1, \Psi_2, ..., \Psi_n\}$ which induces a partition $\pi(\Psi) = \{m(\Psi_1), ..., m(\Psi_n)\}$ of the universe, for formulas Φ, the conditional entropy $H(\Psi \mid \Phi)$ that reveals the uncertainty of formulas Φ based on formulas Ψ, is defined by Eq (10) (Lin 1998):

$$H(\Psi \mid \Phi) = -\sum_{i=1}^{n} p(\Psi_i \mid \Phi)\log\left(p(\Psi_i \mid \Phi)\right), \qquad (10)$$

where: $p(\Psi_i \mid \Phi) = \frac{|m(\Phi \cap \Psi_i)|}{|m(\Phi)|}$.

If Φ is a certain formula, ($p(\Psi_i \mid \Phi) = 1$ and $p(\Psi_j \mid \Phi) = 0 \ \forall j \in 1{:}\, n$ and $j \neq i$), entropy reaches the minimum value i.e. 0.

3. Mining association rules

By extracting association rules using GrC, rules with minimum entropy and maximum absolute support are extracted and high generality and Coverage are used for determining priority of these rules (Lin 1998).

Figure 1 illustrates the executive steps needed to construct the decision tree for extracting association rules.

4. Mining exception rules

Association rules are not completely accurate and have some deficiencies. It is possible that the association extracted for two concepts by this method may not exist in reality, or there may be some rules that are not extractable by this method (Lin 1998). For example, based on association rule extraction principles, for the two concepts Φ and Ψ, if rule $\Phi \rightarrow \Psi$ has the high absolute support, this rule can be extracted as an association rule, however if Ψ is a concept with high generality, considering the change of support formula, it could be concluded that in reality Φ supports Ψ negatively and association does not exist.

It is also possible that a rule may not have a high generality but may be a suitable rule which has not been extractable via the association rules extraction method (Yao, Yao 2002). Exception rules can be extracted for a rule like $\Phi \rightarrow \Psi$ if formula Φ' is found and added to the initial rule and a converse result to

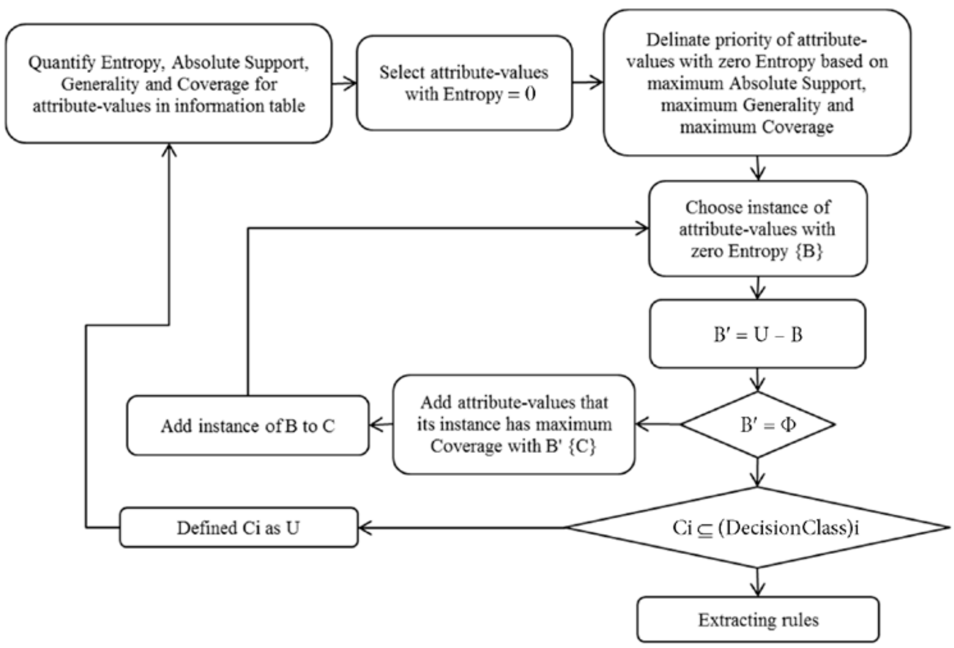

Fig. 1. Granule tree algorithm for mining association rules

the initial rule is obtained for instance, $\Phi' \wedge \Phi \rightarrow \Psi$; in which it has high absolute support and positive change of support, no matter how low the generality is (Skowron, Stepaniuk 2001).

5. Methodology

Data preparation, data integration using Dempster-Shafer theory and construction of a granular tree are discussed in this section.

5.1. Data preparation

In this research, Tehran's seismic vulnerability is assessed based on the assumption of activation of the North Tehran Fault (NTF) and the activation of other faults has been ignored.

Considering the availability of the 1996 census data, the assessment of seismic vulnerability is carried out using the data. And considering the building material and the number of stories in a building functioning as effective parameters in vulnerability assessment, the percentage of materially weak-founded and less-than-4-storey buildings and the percentage of weak-founded buildings of more than 4 stories in any given urban statistical district are assumed as the two major parameters (material and number of stories) effecting the seismic vulnerability. Since building design regulations in Iran were ratified and enforced in 1966, buildings constructed before this date are considered as non-structured buildings. Moreover, the first fortification regulation (safety) against earthquake was drawn up and enforced in 1988. In this research, the two parameters of the percentage of buildings constructed before 1966 and the ones constructed between 1966-1988 are considered as the safety standard parameters. In addition to the building parameters, the average incline of the land and the intensity of earthquake in MMI are considered as other seismic parameters. Table 1 contains seismic information of some randomly selected samples. In this table, for simplification, seismic parameters are summarized as follows:

Slop: Slope

MMI: MMI

Build_less4: Percentage of weak buildings having less than 4 floors

Build_more4: Percentage of buildings having 4 floors and more

Bef-66: Percentage of buildings built before 1966

Bet-66-88: Percentage of buildings built between 1966 and 1988.

5.2. Combination of experts' point of views

For determining physical seismic vulnerability for each sample urban statistical unit, three experts are asked in the fields of civil engineering, seismology and geology to define the physical seismic degree of vulnerability for 50 sample statistical units using numbers between one to five – considering 1, 2, 3, 4 and 5 as respectively very low vulnerability, low vulnerability, intermediate vulnerability, high vulnerability and very high vulnerability. The experts' points of view are demonstrated in Table 1.

The Beynon formula is employed to normalize the expert perspectives. Eq (11) and (12) are used to calculate the basic probability numbers (BPN) for each group of sample units based on expert perspectives (Beynon *et al.* 2001):

$$m(s_i) = \frac{a_i\, p}{\sum_{j=1}^{d} a_j\, p + \sqrt{d}}, \quad i = 1, 2, \ldots d; \qquad (11)$$

$$m(\varnothing) = \frac{\sqrt{d}}{\sum_{j=1}^{d} a_j\, p + \sqrt{d}}, \qquad (12)$$

where p is the weight associated with each expert's point of view, d is the number of unit groups based on each expert's point of view, a_1, a_2, …, a_d are the relative vulnerability values of each group, $s_1, s_2, \ldots, s_d$ are the group of blocks and $\varnothing$ is the ambiguity for each expert's point of view.

Each expert is considered as an independent source (evidence). Using the Dempster-Shafer rule of combination demonstrated in Eq (4), the expert points of view are combined to reach a unique degree of seismic vulnerability. For example, regarding each expert's idea and assuming that each expert's point of view has the same weights, the BPN for the subsets based on expert 1's point of view using the Beynon formulas are computed as illustrated in Table 2.

Based on the computed BPNs, the combination of expert's remarks by applying Eq (4) is determined. Table 3 presents the combination of remarks of expert 1 and expert 2.

Table 4 contains the result of combination of experts 1 and 2's remarks by expert 3's point of view. The final results of the combination are used as the input of the granule tree.

5.3. Extracting association rules

Based on the association rules mining method using the GrC model discussed in Section 4, the extracted rules employing the granular tree to determine the

Table 1. Information table of sample areas

S_num	Slope	MMI	Buil_less4	Bef-66	Bet-66-88	Buil_more4	E1	E2	E3
1	4	3	2	1	1	1	4	4	5
2	4	4	1	1	4	1	5	5	4
3	4	4	3	2	3	1	5	5	5
4	2	4	2	1	3	1	5	5	3
5	3	4	1	1	1	3	4	3	4
6	1	3	3	1	3	1	4	4	4
7	2	3	1	2	2	2	4	4	3
8	1	3	2	1	4	1	5	5	3
9	2	3	1	1	3	1	3	3	2
10	1	4	4	2	2	2	5	5	5
11	1	4	2	2	2	1	2	3	2
12	2	3	2	1	4	1	3	3	4
13	2	3	1	1	3	1	2	2	2
14	1	3	2	2	4	1	3	3	5
15	4	3	1	1	1	1	3	3	3
16	2	3	2	1	4	1	3	3	3
17	1	3	2	1	4	1	3	3	3
18	1	2	3	2	3	1	4	3	4
19	1	2	4	2	3	1	5	4	5
20	1	1	3	3	2	1	4	3	4
21	1	2	4	4	1	3	5	5	4
22	1	2	3	4	1	3	5	5	5
23	1	2	4	3	1	3	5	5	5
24	1	2	3	3	2	3	5	5	4
25	1	3	4	3	2	1	5	5	5
26	1	2	4	4	2	1	5	4	5
27	1	2	4	4	1	1	5	5	5
28	1	2	4	3	2	1	5	5	4
29	1	2	4	4	1	1	5	5	5
31	1	1	3	1	4	1	4	4	3
32	1	1	2	1	3	1	4	4	3
33	1	1	3	2	3	1	4	4	4
34	1	1	3	3	2	1	4	4	3
35	1	2	1	1	4	1	3	3	2
36	1	2	4	1	4	1	5	5	5
37	1	1	4	2	3	1	5	5	5
38	1	2	2	2	4	3	4	5	4
39	1	1	3	4	1	1	5	5	5
40	1	1	4	1	4	1	5	5	5
41	1	2	3	1	4	1	4	4	5
42	1	1	3	1	4	1	5	5	5
43	1	1	2	1	4	1	4	4	4
44	1	2	3	1	4	1	4	4	3
45	1	2	4	4	1	1	5	5	5
46	1	2	4	4	1	1	5	4	5
47	1	2	3	3	2	2	5	4	5
48	2	3	3	1	3	1	5	5	5
49	1	2	4	2	3	1	5	5	4
50	1	3	3	2	3	1	5	5	5

Table 2. Expert's 1 point of view

Subsets	Calculation	BPN
$\{u_9, u_{11}, u_{13}, u_{35}\}$	$\frac{(2)(1)}{\sum(2)(1)+(3)(1)+(4)(1)+(5)(1)+\sqrt{4}}$	0.125
$\{u_4, u_7, u_8, u_{15}, u_{16}, u_{17}, u_{31}, u_{32}, u_{34}, u_{44}\}$	$\frac{(3)(1)}{\sum(2)(1)+(3)(1)+(4)(1)+(5)(1)+\sqrt{4}}$	0.1875
$\{u_2, u_5, u_6, u_{12}, u_{18}, u_{20}, u_{21}, u_{24}, u_{28}, u_{33}, u_{38}, u_{43}, u_{49}\}$	$\frac{(4)(1)}{\sum(2)(1)+(3)(1)+(4)(1)+(5)(1)+\sqrt{4}}$	0.25
$\{u_1,u_3,u_{10},u_{14},u_{19},u_{22},u_{23},u_{25}, u_{26}, u_{27},u_{29}, u_{30},u_{36},u_{37}, u_{39}, u_{40}, u_{41},u_{42}, u_{45},u_{46}, u_{47}, u_{48}, u_{50}\}$	$\frac{(5)(1)}{\sum(2)(1)+(3)(1)+(4)(1)+(5)(1)+\sqrt{4}}$	0.3125
$\{\emptyset\}$	$\frac{\sqrt{4}}{\sum(2)(1)+(3)(1)+(4)(1)+(5)(1)+\sqrt{4}}$	0.125

Table 3. Combination of experts1 and 2's remark

y	m(y)
$\{u_{13}\}$	0.0698
$\{u_{11}\}$	0.0930
$\{u_9,u_{12},u_{14},u_{15},u_{16},u_{17},u_{35}\}$	0.1221
$\{u_5,u_{18},u_{20}\}$	0.1512
$\{u_1,u_6,u_7,u_{30},u_{31},u_{32},u_{33},u_{34},u_{41},u_{43},u_{44}\}$	0.1860
$\{u_{38}\}$	0.2209
$\{u_{19},u_{26},u_{46},u_{47}\}$	0.2209
$\{u_2,u_3,u_4,u_8,u_{10},u_{21},u_{23},u_{24},u_{25},u_{27},u_{28},u_{29},u_{36},u_{37},u_{39},u_{40},u_{42},u_{45},u_{48},u_{49},u_{50}\}$	0.2616
$\{\emptyset\}$	0.0233

Table 4. Final combination

y	m(y)
$\{u_{13}\}$	0.0221
$\{u_{11}\}$	0.0294
$\{u_9,u_{35}\}$	0.0386
$\{u_{15},u_{16},u_{17}\}$	0.0483
$\{u_{12}\}$	0.0579
$\{u_{14}\}$	0.0676
$\{u_5,u_{18},u_{20}\}$	0.0717
$\{u_7,u_{31},u_{32},u_{34},u_{44}\}$	0.0735
$\{u_6,u_{33},u_{43}\}$	0.0882
$\{u_1,u_{30},u_{41}\}$	0.1029
$\{u_{38}\}$	0.1048
$\{u_{19},u_{26},u_{46},u_{47}\}$	0.1222
$\{u_4,u_8\}$	0.1034
$\{u_2,u_{21},u_{24},u_{28},u_{49}\}$	0.1241
$\{u_3,u_{10},u_{22},u_{23},u_{25},u_{27},u_{29},u_{36},u_{37},u_{39},u_{40},u_{42},u_{45},u_{48},u_{50}\}$	0.1448
$\{\emptyset\}$	0.0041

seismic vulnerability of urban areas is illustrated in Figure2.

5.4. Extracting exception rules

Based on the information presented in Table 1, some exception rules which could be extracted by employing the GrC methods for seismic vulnerability assessment are shown in Figure 3.

For clarifying an exception rule extracted from IF Then statement (if MMI = 2(Φ) then decision class = 5 (Ψ)) is determined as follows:

Absolute support of this rule is calculated as:

$$AS(\text{MMI} = 2 \rightarrow \text{class} = 5) = 14/19 = 0.7368$$

By considering Φ' as (build_less4=1) and its addition to Φ, this concept reaches maximum absolute support 1 for decision class=3. Absolute support and change of support of this rule is calculated as below:

$$AS(\text{MMI}=2 \wedge \text{build\_less4} = 1 \rightarrow \text{class3}) = 1 \text{ and}$$
$$CS(\text{MMI}=2 \wedge \text{build\_less4} = 1, \text{class3}) = 0.86$$

Taking into account the exception rule extraction method, the concept (Φ^ Φ′) that has the high absolute support and positive change of support, is mined as exception rule for rule Φ→ Ψ.

Extracted association rules and exception rules are employed to assess the seismic vulnerability. Figure 4 demonstrates the concluded seismic vulnerability map of Tehran.

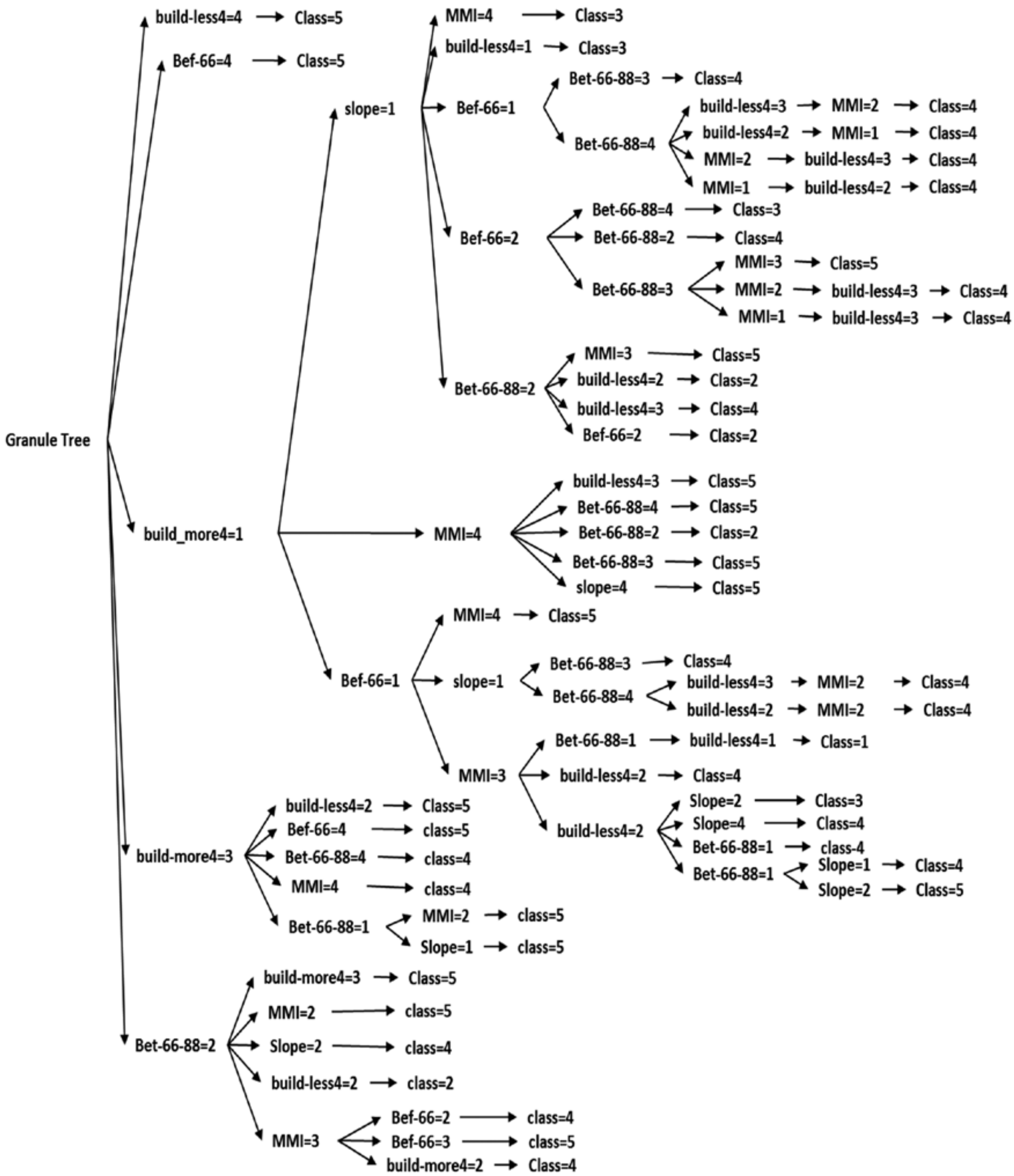

Fig. 2. The granule tree for extracting association rules

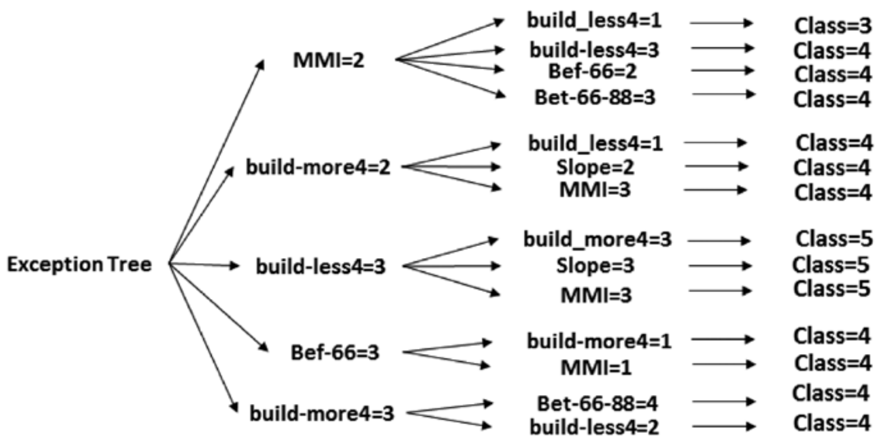

Fig. 3. Granule tree for extracting exception rules

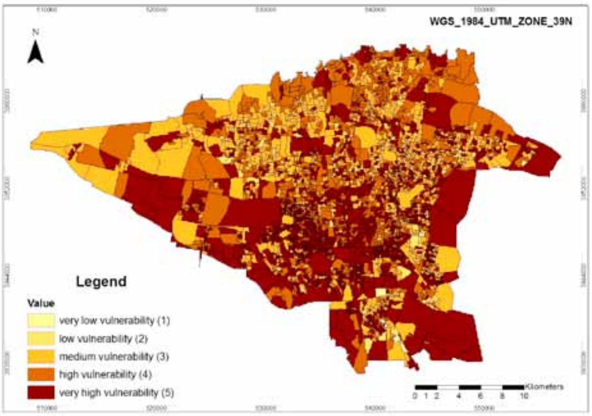

Fig. 4. Tehran's seismic vulnerability map using association rules and exception rules

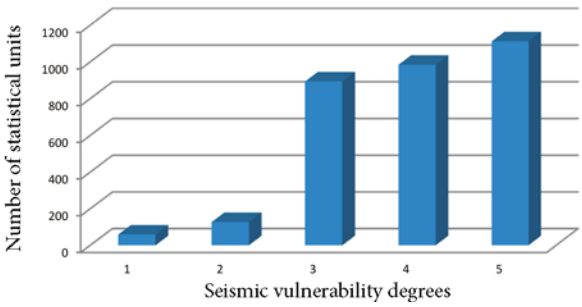

Fig. 5. Number of statistical units for different seismic vulnerability degrees of the map produced based on the association and exception rules

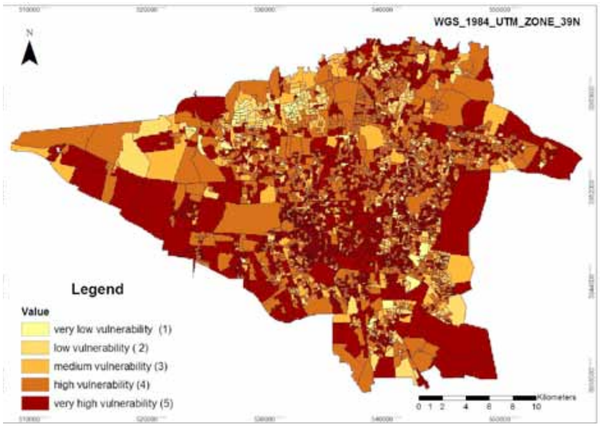

Fig. 6. Tehran's seismic vulnerability map using association rules

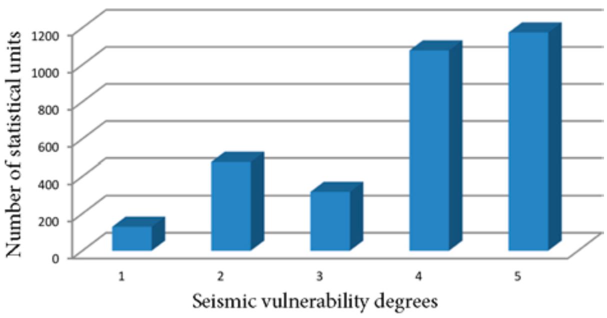

Fig. 7. Number of statistical units for different seismic vulnerability degrees for map produced based on association rules

6. Discussion

By looking at the resulting seismic vulnerability map of Tehran, it can be determined that 35% of statistical units have very high vulnerability, 31% have high vulnerability, 28% have medium vulnerability, 4% have low vulnerability and 2% have very low vulnerability. Based on these results, most statistical units have very high vulnerability and are located in south of Tehran.

Figure 5 shows the number of statistical units for each vulnerability degree.

In reference to the information of Figure 5, most of the statistical units of Tehran, have medium to very high seismic vulnerability degree and only 6% of these statistical units have low and very low vulnerability degree. Figure 6 represents Tehran's vulnerability map based on association rules extracted by the granular computing model standing on one expert's perspective.

The results of seismic vulnerability demonstrated in Figure 6 are strongly related to experts' remarks and the uncertainty of this map is high. The results of this map represent that 37% of statistical units have very high vulnerability, 34% have high vulnerability, 10% have medium vulnerability, 15% have low vulnerability and 4% have very low vulnerability. Figure 7 shows the number of statistical units for each seismic vulnerability degree.

According to the information presented in Figure 7, most of the statistical units of Tehran are classified in high and very high vulnerability classes.

Accuracy of the classification of statistical units is calculated based on $\frac{k}{k+n}$ (Pedrycz *et al.* 2008), where k is the statistical units correctly classified and n denotes the incorrectly classified units. By selecting sample data as test data, the final accuracy is estimated. The final accuracy in the seismic vulnerability map employing association rules and exception rules using three experts' points of views is estimated as 83%. This quantity for the seismic vulnerability map using association rules and one expert's perspective is estimated at 62%. These results confirm that using a number of experts' points of views instead of one expert's perspective and extracting the exception rules coupled with the association rules, decreases the uncertainty to a great extent.

Conclusion

The problem of assessing the seismic vulnerability is a multi-criteria decision making problem and because of its dependence to parameters and experts' remarks, it is always accompanied with uncertainties. Utilizing a number of methods to minimize existing uncertainties in this problem could make the decision making in disaster management more reliable and precise.

In this research, by employing various experts' remarks and their combination using DST, the uncertainty related to experts' remarks from both misgiving and incompatibility aspects is reduced. Moreover, in this research, granular tree is utilized in order to extract rules with minimum incompatibility from the information table provided by the experts. In order to extract accurate association rules, in addition to entropy and absolute support, change of support is used. In addition to association rules, exception rules extraction led to worthy support to extract effective rules to define seismic vulnerability.

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