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Post Seismic-Activity Rescue Prioritization

Using Multi-Criteria Decision Aid

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MATH-H405: Decision Engineering

Contents

List of Figures

List of Tables

1 Introduction

Natural disasters such as earthquakes can cause devastating destruction. They often resulting in massive casualties and economic loss. Many Researchers projects have been dedicated to estimating casualties of earthquakes such as the work of Yamazaki et al. [19] or the technical report by Jaiswal et al. [10]. Moreover, there has been many research regarding rescue efforts post earthquakes like the work of Schultz et al. [16] or the guidelines by Fuse et al. [4]. In summary the main goal of the mentioned research projects is to reduce future earthquake trauma as well as to improve the structure and scheduling of the excising rescue missions.

In addition, in majority of the mentioned cases, the main source of collected data are the medical institutions and as explained by kang et al. [15] these kinda data is subjected errors due to the chaotic state of hospital after an earthquake. Moreover, there are many more factors which can be considered in order to reduce the number of casualties after an earthquake. For example, fear and anxiety can increase the number of casualties and effect individual behaviours during rescue missions. Furthermore, victims behaviour can vary depending on their level of education and whether they have received training regarding natural disasters.

In the past decade, researchers designed some sophisticated solutions for determining the seismic risk (see Lin et al.[13]). However, most of these solutions are complex and too expensive(with regards to the time as well as the cost) to be employed by the decision makers. According to Giovinazzi et al.[6], since the post earthquake trauma depends on many variables(criteria), disaster relief deployment programs can be considered a Multi-Criteria Decision Aid(MCDA) problem. Costa et al [3] employs MCDA to priorities tunnels and bridges for the post earthquake disaster. Hosseini et al. [9] focuses using MCDA on temporary housing during the disaster relief phase. In addition, multi-criteria seismic risk assessment approaches such as the work of Sinha et al. [17] are gaining popularity.

2 Problem Statement

To the best of our knowledge non of the mentioned existing work employ the PROMETHEE method to priorities seismic rescue relief missions prior to an earthquake. The only existing work we were able to obtain, focuses on identifying vulnerable buildings or seismic retrofitting[2]. In this project, we are going to focus on prioritizing regions based on some criteria prior to an earthquake. Therefore, once the disaster strikes, the decision makers can prioritize the deployment of their rescue teams according to our predictions.

As a proof of concept, we are going to use D-SIGHT web-based software [1] to prioritize a subset of multiple regions within an area that the earthquake might happen. In our proof of concept we decided to priorities regions within a country. It is worth mentioning that in a real earthquake scenario, this method can be applied to any level of granularity and is not limited to our subset. However, for the matter of simplicity we decided to focus on cities within a country.

In order for a country to be selected for our proof of concept it must fit the following requirements:

Requirement 1. *Low economical states.* According to Sinha et al. [17] developed countries may not receive a significant benefit from such prioritization solutions, since they tend to suffer less during natural disasters due to their investment in infrastructure and education. Moreover, most developing countries, already have some sort of post disaster rescue plan for their vulnerable regions. It is mostly in developing countries with low economical states where resources are limited they need to be prioritized.

Requirement 2. *Available data for all of our defined criteria.* This requirement is crucial to make sure we will have enough data for each of our criterion. In order to perform pairwise test, non of the criteria should contain missing values.

Requirement 3. *Prior records of seismic activities.* This requirement is simply defined to make sure our solution has the potential of the real life application. For example if a country suffered an earthquake and the lack of prioritization for vulnerable regions during rescue missions created devastating results, such country fits this requirement for the proof of concept.

3 Defining Alternatives

Earthquakes normally happen within regions. These regions can be divided into multiple sub-regions depending on the magnitude of the earthquake. Therefore, our alternatives here are sub-regions (i.e. cities) withing a region (i.e. country) and we would like to prioritize them. Although, we only chose a selected number of cities for our proof of concept, our approach by no means is limited to the number of cities or even regions. One can easily replace our alternatives with regions within a city or increase/decrease the number of cities within a country. Nevertheless, as long as the criteria and the requirements are remaining untouched, our approach should be applicable in any level granularity for alternatives.

[1] https://web.d-sight.com/

4 Defining Criteria

Kang et al. [15] identified the demographic information among the top main causes of trauma post earthquake. In their study Kang et al. found, the part of the population younger than 15 or the the part above the 65 years of age, are the most vulnerable to injury during an earthquake. They also found the female to male ratio has a correlation with the number of casualties. Hosseini et al. [9] defined the type of the land and the material used in buildings as the main factors for the damages caused to buildings during earthquake. Moreover, according to Girty [7], there are always other earthquake hazard such as flood, fire and liquefaction which mostly effect regions with higher population density. In addition, Hassanzadeh et al. [8] studied the impact of factors such as the level of education in the affected area, access to the main cities as well as reliable roads with the number of causalities.

Inspired by some of our collected related works, we defined our criteria under three categories. These categories are: *Geographical information of the region*, *Building types in the region*, *Demographic information of the region.* In the upcoming sections we will go through the criteria defined for each of these categories.

4.1 Geographical Information of the Region

Geographical Region: This criteria is meant to indicate the nature of the land in which a particular region is located. The different kind of landscape of the area is correlated to the damage and trauma caused in a region. Moreover, reaching mountains is always more difficult for rescue teams than flat lands. Therefore, mountain regions may need higher priority since they might experience more damage and it is harder to reach them during rescue without government aid (e.g. air-support).

Direct access to the capital. In here we decided to simplify the access to the big cities to direct access to the capital. We assumed all the resources and rescue teams are deployed from the capital instead of neighbouring big cities. In a real life scenario, one can simply increase the complexity by considering all of the neighbouring big cities related to a region and then measure whether that region has any direct access to at least one of those big cities.

Number of emergency roads. The emergency roads must not contain any tunnels or bridges. According to Costa et al. [3] bridges and tunnels are considered hazards during earthquakes and roads containing such hazards, either need to be avoided or prioritized based on the amount of damage they can take.

4.2 Building Types in the Region

According to Okada et al. [14] the type of the material used in a building can impact the damage pattern of that building during a seismic activities. We decided to select three of the most vulnerable materials used in a building (i.e. mud, wood and unbaked Brick). A region with higher number houses built with weak materials, has a higher priority in our solution.

4.3 Demographic Information of the Region

Age. The age has an influence on the strength, mentality and the ability to adapt of people (see Kang et al. [15]). Moreover, according to Kang et al. people under 15 and above 65 are the ones most likely to be injured. Therefor, we decided to define three criteria for age. These criteria are people under the age of 15, between the age of 15 and 35 and the ones older than 65. It is worth mentioning that during our literature review, we did not find any information regarding the significance of people aged between 35 and 65 and their impact on the number injuries during an earthquake. Therefore, we did not include this criteria.

Number of population. We decided to include the population of each region since in the previous related works(e.g. [15]), population of a region is also correlated to the number of casualties.

Sex ratio. The ratio of women to men is also correlated to the number of casualties. Regions with higher ratio of women to men are shown to have bigger casualties.

Density of the population. The density of population indicates the number people living per square kilometers. Therefore, the higher the density of the population of a region the more chance of casualties in that region.

Education. General education as well as, natural disaster training are shown to have impact on the number of casualties during an earthquake. Moreover, it has been shown by studies (e.g. [15]) that people with the level of education below high school, are the most vulnerable during earthquakes. We decided to have the number of people that did not attend high school as a criteria. In addition, to simplify our problem we also made an assumption that people who did not attend high school, already did not receive any training regarding natural disasters. However, decision makers can always include the statistics regarding natural disaster training for each region as a separate criteria.

We would like to mention that we further slightly modified these categories and divided them into four categories. The decision for the modification of the categories was done during our modeling phase when we needed to have a better weight distribution.

5 Data Collection

Year	Country	Requirement 1	Requirement 2	Requirement 3	Death
2017	Mexico	Yes	No	Yes	370
2016	Italy	No	Yes	Yes	300
2016	Ecuador	Yes	No	Yes	650
2015	Afghanistan	Yes	No	Yes	400
2015	Nepal	Yes	Yes	Yes	9000
2014	China	Yes	No	Yes	600
2013	Pakistan	Yes	No	Yes	825
2012	Iran	Yes	No	Yes	300
2011	Turkey	Yes	No	Yes	600
2011	Japan	No	Yes	Yes	15690
2011	Newzeland	No	Yes	Yes	180
2010	Chile	Yes	No	Yes	500
2010	Haiti	Yes	No	Yes	316000
2008	China	Yes	No	Yes	87600

Table 1: The 14 deadly earthquake of last decade considered for this project.

We have considered a list of 14 deadly earthquake of last decade provided by Reuters[2]. Table 1 shows the results of investigation for each countries in regards to our requirements. In addition, the number of death is cross-validated with USGS Earthquake Hazards Program,[3] just to make sure they are reliable. From Table 1 we can see that the 2015 Nepal earthquake is the the only candidate which matches all the Requirements. It is worth mentioning that for some of our candidates we found data for almost all of our criteria and we only had to reject them due to lack of data for only one criteria. For example, in case of both 2014 and 2008 earthquakes in China we were not able to find sufficient data regarding whether some of the roads contained bridges or tunnels. We also considered the 2013 Lushan earthquake which was the subject of study by Kang et al. [15], however, we decided to stay with Nepal since the magnitude and the number of casualties during the 2015 Nepal's earthquake is significantly bigger than the Lushan's earthquake.

Nepal earthquake killed nearly 9,000 people and injured nearly 22,000. Many people were made homeless and in some case the entire village flattened [45]. Some experts like Dr. Alexandra Titz[6] argue that beside the demographic, political and economical factors the lack of prioritization during aid had a significant impact on the number of casualties. Therefore, we believe that with employing the PROMETHEE method we are able to provide a prior MCDA prioritization

[2]https://www.reuters.com/article/us-iran-quake-global/timeline-worlds-14-deadliest-earthquakes-of-last-decade-idUSKBN1DD257

[3]https://earthquake.usgs.gov/earthquakes/eventpage/us1000e9j2executive

[4]https://web.archive.org/web/20150504211559/http://www.ekantipur.com.np/the-kathmandu-post/2015/04/29/news/great-earthquake-wipes-out-barpak/275829.html

[5]http://archive.nepalitimes.com/article/nation/langtang-destroyed-in-earthquake,2205

[6]https://www.fau.eu/2015/05/21/news/why-was-nepal-badly-prepared-for-the-earthquake-on-25-april-2015/

Figure 1: 2015 Nepal earthquake regions adopted from Britannica.

proof of concept for Nepal's post earthquake rescue mission.[7]

We used three official statistical reports provided by the government of Nepal to collect data for our criteria. In order to collect the data regarding our demographic categories as well as the building types in each region, we used the national population and housing census [11]. in order to make sure our data is not outdated, we then applied some of the necessary updates to our data from the 2015 statistical year book [1]. In order to obtain our geographical information we had to use two different documents. First we used the statistics of local road network [5] then we and then we had to cross-compare some of the tables we had regarding our roads with Nepal's statistical year book[1]. All of the mentioned document are freely available online and are provided by the Central Bureau of Statistics of the Nepalese government.

Moreover, we would like to mention that we did not include all the regions affected during the actual Nepal earthquake of 2015. There were many cities and villages were affected during that earthquake shown in Figure 1 which is adopted from Britannica online [8]. However, for simplicity, we picked one representing area from each major region. The selected cities are: *Surket Valley*, *Dang Valley*, *Rupandehi*, *Nawalparasi*, *Parsa* and *Ruatahat*.

[7]https://earthquake-report.com/2015/05/03/deadly-earthquake-nepal-25042015-archived-part-nr-5-april-29-0000-until-april-30-2400/

[8]https://www.britannica.com/topic/Nepal-earthquake-of-2015

6 Tools and Software

We first collected all of our data in Microsoft Excel and then we uploaded our data in D-sight[9]. D-sight offered us different tabs to enter our weights and preference functions. Moreover, our analysis is done using score tables and graphs we obtained from D-sight.

7 Modeling

When we defined our criteria, we decided to categorize them in three categories. However, we decided to dived our categories into four categories instead of three. This way, we are able to assign better weights to our categories and their criteria. Therefore, we have *geography*, *age*,*building type* and *Other Demographic Information* as our categories. Table 2 shows categories as well as the criteria for each category. In summary, we decided to divide our *demographic information of the region* category into two new categories (i.e. age and other demographic information). Age has a much bigger impact on the number of victims than the rest of the demographic information. Moreover, we wanted to be able to compare the age with the other demographic information during our analysis phase.

7.1 Geography

We simply renamed our former categories *Geographical Information of the region* into geography. Geography has the lowest weight among all the categories(i.e. 10.52%). This decision is made based on our related work investigation. The three criteria in geography remain the same as before and are the following:

The Geographical Region: Geographical region for Nepal can be Terai(special type of flat land in Nepal), hill or mountain with Terai(value equal to 0) showing the least vulnerable and mountain (value equal to 2) the most vulnerable. Therefore, the value of this criteria needs to be maximized. Moreover, we used our custom qualitative scale with Terai having the lowest score and mountain having the highest. The preference function here is the usual. This criterion has the highest weight (i.e. 50%) since the the type of the land can have the biggest impact.

Direct Access to the Capital: Here "No" has a value of 0 and "Yes" has value of 1. The criterion is minimized because the region with no access to the capital have higher priority. We also chose the usual preference function here. This is our least important criterion in the geography category with the lowest weight of 15%.

Number of emergency roads: Number of emergency roads to a city is the subtraction of

[9] http://www.d-sight.com/

	Geography(10.52%)			Age(31.19%)		
	Geographical Region	Direct Access to the Capital	Number of Emergency Roads	0-15	15-35	65+
Surkhet Valley	Hill	Yes	3	100015	123272	13576
Dang Valley	Terai	No	2	165834	229390	22573
Rupandehi	Terai	Yes	5	299508	320228	43093
Nawalparasi	Terai	No	1	214487	227539	35260
Parsa	Terai	No	4	228797	199819	24576
Rautahat	Mountain	No	0	278410	212372	31602
Maximize/Minimize	Maximize	Minimize	Minimize	Maximize	Maximize	Maximize
Weight	50%	15%	35%	50%	15%	35%
Function	Usual	Usual	Linear	Linear	Linear	Linear
Indifference Threshold	N/A	N/A	0	10000	190000	500
Preference Threshold	N/A	N/A	1	30000	191000	2000

	Building Type(35.03%)			Other Demographic Information(23.26%)			
	Mud	Wood	Unbaked Brick	Population	Sex ratio Male/Female	Density Population (#People / km²)	Educated Below High school
Surkhet Valley	41959	14633	833	350804	0.93	143	178192
Dang Valley	52361	4914	23294	552583	0.89	187	238109
Rupandehi	36760	4151	2291	662829	0.96	647	438367
Nawalparasi	31624	8220	1472	643508	0.89	298	512049
Parsa	2749	4278	127	453192	1.08	444	245175
Rautahat	11828	5698	512	686722	1.04	610	202988
Maximize/Minimize	Maximize	Maximize	Maximize	Maximize	Minimize	Maximize	Maximize
Weight	54.54%	13.64%	31.82%	9.09%	31.82%	36.36%	22.73%
Function	Linear	Linear	Linear	Linear	Linear	Linear	Linear
Indifference Threshold	500	1000	300	100000	0.02	44	9000
Preference Threshold	5000	3000	1000	200000	0.05	160	80000

Table 2: Value of the criteria

the number of roads with bridges and tunnels from the total number of roads entering the city. We also needed to minimize this criterion since the lower the number of emergency roads entry a city the higher priority it will have to the federal government. Cities without any emergency road might need to receive all of their aid via helicopters. Here the function is linear. The preference threshold has a value of 1 because the difference of one can make a big difference. This is the second most important criterion in the category (i.e. with the weight of 35%).

7.2 Age

The age has an influence on the strength, mentality and the ability to adapt of people. However, during our related work investigation we concluded that age still cannot be the most important criteria since building type still has a bigger impact on the number of victims. Therefore, Age is our second most important category(i.e. with weight of 31.19%). For all the criteria in the category we decided to choose the linear preference function and the indifference threshold and preference threshold are chosen based on how close the values are to one another, as well as, how much difference we considered significant. We distributed the weights based on the related works with population under 15 years of age having the highest weight(i.e. 50%) and people between 15 and 35 the lowest weight(i.e. 15%).

0-15: The number of children between 0 and 15 have been calculated according to the data. This category needs to be maximized. The function is linear and the indifference and preference threshold are respectively 10000 and the 30000. why?

15-35: This range of age is the least important compared to the other range due to their strength and then their ability to survive after a natural disaster. That is why this criterion has a weight of only 15% . The thresholds are chosen in a way that only the significant difference between two criteria is will have an impact on the ranking. This value still needs to be maximized since under any circumstance, bigger population of any age is correlated to the number of victims during an earthquake.

More than 65: This age range is the second most important age range based on our related works. The preference function is linear but the thresholds are small since values are not so close to one another.

7.3 Building Type

This is the most important category with the highest weight(i.e. 35%). As we mentioned in the preview section, we only chose the weak materials. Therefore, the higher the number of buildings with weak materials the higher their priority becomes. All the criteria need to maximized and the all the preference functions are linear.

Mud: This is the cheapest and the most common material used in buildings in Nepal. This is just dried mud utilized to build walls. Mud is also the least stable material due to its stiffness. This is the reason why the weight exceed 50%. The indifference threshold is chosen to be 500 since the difference between some of the data is not significant. Moreover, we heuristically found number 5000 works best for our preference threshold. This was also expected since many houses are made from Mud in Nepal.

Unbaked brick: Backed brick are used everyday in construction. It is a mix of different component that is meant to be harden when it is backed. This has the second place in the weight ranking of the building type with a significant difference between the thresholds in regards to the different number of unbaked brick used.

Wood: Wood has been used for many years as a construction material in Nepal. Although it is the second most used material in Nepal, it has the least affect on the number of casualties during an earthquake in comparison to the above criteria. With a linear function, indifference threshold of 1000 and a preference of 3000, those number were chosen to have an preference only when there is a big difference.

7.4 Other demographic Information

This category is placed as the third rank (i.e. weight is 23.26%) for its impact on the casualties during an earthquake. We decided to combine lesser important demographic criteria together. Except the sex ratio all the other criteria in this category are maximized.

Number of Population: This criterion has the lowest weight because it does not have a big influence in the decision compared to the other criteria. We included this criteria since most of our related works suggested some correlation between the population and the trauma post earthquake. However, since the age of the victims plays a bigger role than solely the population of a country, we reduce the weight given to this criteria. The function is linear and have a relatively small difference between the indifference and preference threshold compared to the number of population of each city. We waned to make sure bigger differences between the population between alternatives receive higher priority and the numbers which are closer together are considered indifferent.

Sex Ratio (Male/Female): The ratio is minimize because as we explain in the previous section, alternatives with bigger female to male ration have a higher priority. We could only find data for male to female sex ratio. Therefore, we decided to minimize this criteria. The function is linear. The indifference threshold s 0.02 and the preference threshold is 0.05. Those values were chosen to be small because the difference between the ratios has a big influence on the final decision.

Density of Population: This criterion has the highest weight (i.e 36%) since it has the biggest impact on the number of victims during an earthquake compared to other criteria in this category. We chose our indifference and preference thresholds to make sure bigger values get higher priority. However, since the correlation of the density population with the number of victims is rather linear we did not choose the Gaussian preference function.

Education: The number of people that did not attend high school is almost half of the population in each zone and is maximize. The function is linear with a indifference threshold of 9000 and preference threshold of 80000.

8 Analysis

Our analysis are based on the results we obtain from the D-sight website. In this section we first analyze our ranking, then find our conflicting criteria and we finilise our analysis with robustness analysis.

8.1 Ranking

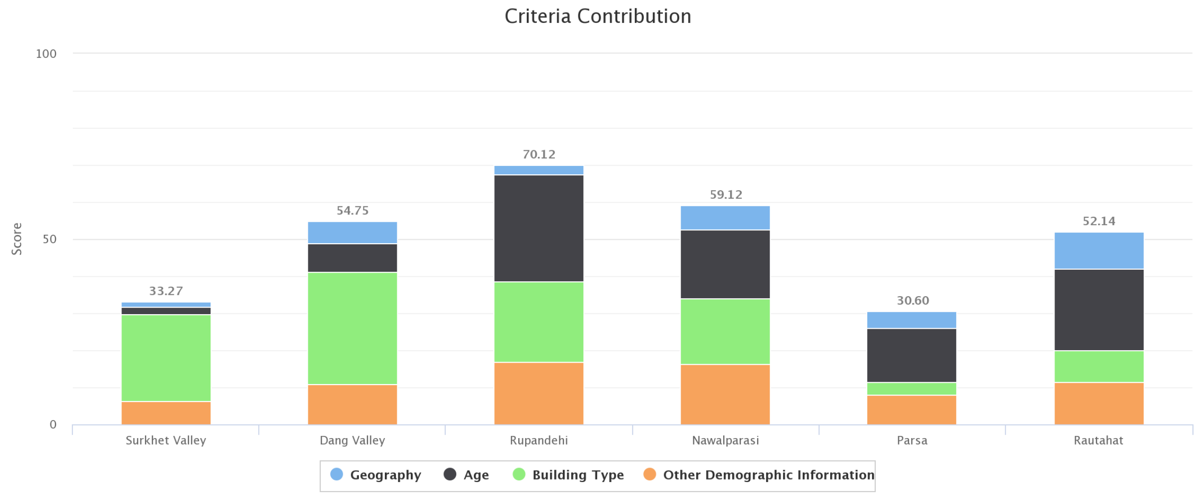

Figure 2: Criteria contribution

Figure 2 shows the overall score as well as the contribution of each criteria to that score for each alternative. During our analysis we realized, no alternative outranks other alternatives in all the criteria. Therefore, a naïve approach here will be to just add all the alternatives to our Pareto-optimal frontier. However, Based on Figure 3 we realized that Parsa is dominated by Rautahat. In addition, Surkhet Valley is dominated by the Dang Valley. Therefore, we can conclude that if nothing else changes and the decision maker completely agrees with our modeling we will have a Pareto-optimal frontier which contains all the alternatives except Parsa and Surkhet Valley. Moreover, if we base ourselves on the overall ranking we can conclude that Rupandehi is the best alternative. The overall ranking for each alternative is shown in Table 3. Nevertheless, as we mentioned we can also not include Parsa and Surkhet Valley in our analysis since they are being dominated. We leave this decision to the decision maker since in case of natural disaster decision makers might want to have as many information as possible.

The column chart in Figure 3 shows the scores by categories. A decision maker is provided with a choice of selecting an alternative based on different criteria. For example if they only consider the building type, then, based on Figure 3, Dang Valley is the best alternative.

8.2 Global Visual Analysis

In order to analyze the dependency or the conflict between our criteria we used the GAIA visualization tool provided by the D-sight. This way we can have a more in depth understanding over the decision process.

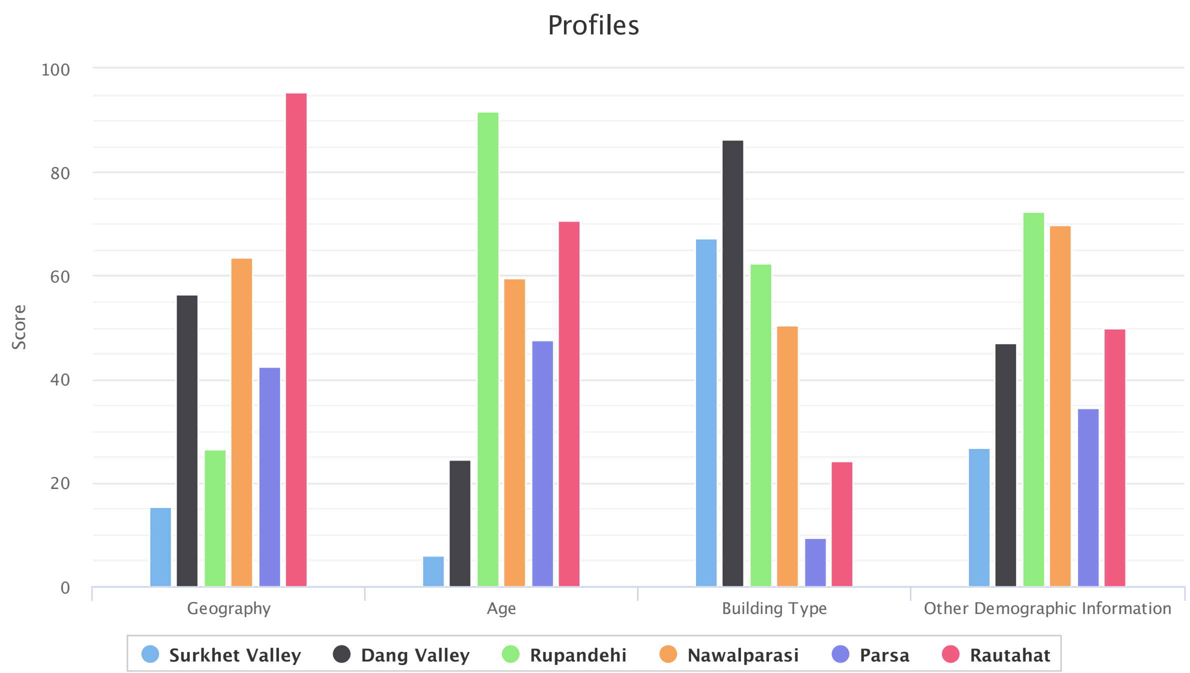

Figure 3: Ranking graph

Ranking	City	Score
1	Rupandehi	70.12
2	Nawalparasi	59.12
3	Dang Valley	54.75
4	Rautahat	52.14
5	Surkhet Valley	33.27
6	Parsaa	30.6

Table 3: Ranking by order

We can see from Figure4 that we have 5 vectors for our criteria as well as 6 points for our alternatives. The value of delta is more than 70% which means we have very few information loss (based the work of Lidouh et al. [12]) and the GAIA plane provides a reliable representation of our decision problem with the quality of 80.50%.

In Figure 4, we can see that building type and geography are conflicting criteria since the corresponding vectors for each one of them are on the opposite direction. This is an expected phenomenon since houses built on the mountain regions are more robust due to the type of materials used in their built. Building type here is being maximized. However, in previous sections we mentioned that we are maximizing the building type based on the number of houses built using weak material. Therefore, Building type and Geography can be considered as conflicting criteria.

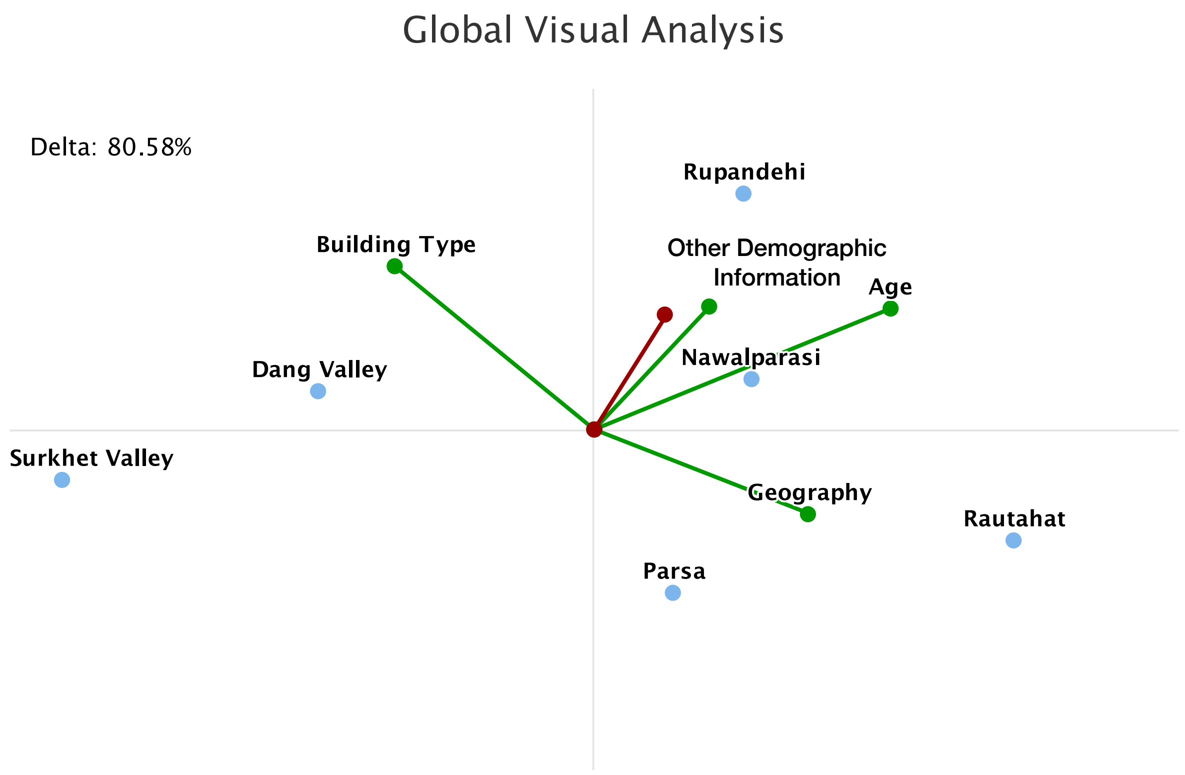

Figure 4: GAIA of categories

Figure 4 also shows age and Other demographic information as similar criteria. This is also expected since age and other demographic information used to be united in the same category. We simply split them to be able to have better analysis as well as being able to assign better weights to them.

We can also see that the decision stick (unit vector of weights) is pointing to the same direction as the alternative with the highest ranking (i.e. Rupandehi). In addition, in the GAIA space, the order of the overall ranking of the alternatives is not the same as the ones provided in Table3. In the GAIA space Parsa is the best alternative and Surkhet Valley is the worst. Moreover, if we select our best and worst alternatives based on categories (e.g. age), then the results are still conflicting with our previous findings (see Figure 2). This kind of results might be due to the dimensionality reduction that happens in the GAIA space since we go from a multi-dimensional space to a 2D space.

9 Stability

There is a chance that the decision maker has a different preference for the weights regarding each criteria. This is where the robustness of the decision can be analyzed. Therefore, by doing a stability analysis, it is possible to determine the lower and upper bound of each criterion that could have been chosen differently without influencing the ranking.

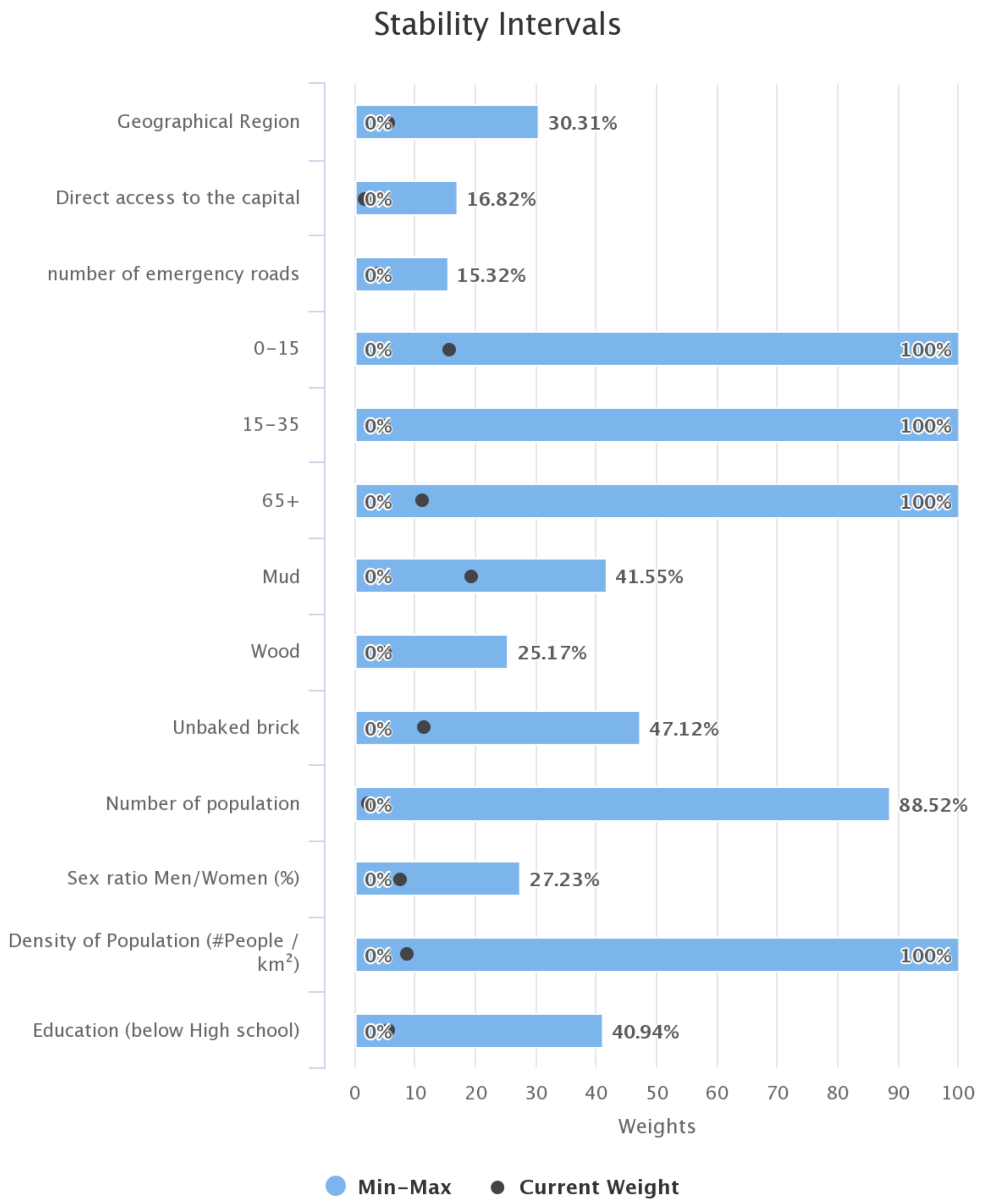

Figure 5: Stability of criteria

With the graph on figure 5, it is noticeable that since the different ages and the density of population have a lower bound of 0 and an upper bound of 100, the weight of those criteria could have been chosen differently and would not have an impact on the ranking. Except the "Number of Population", all the other criteria have a range that is less than 50%.

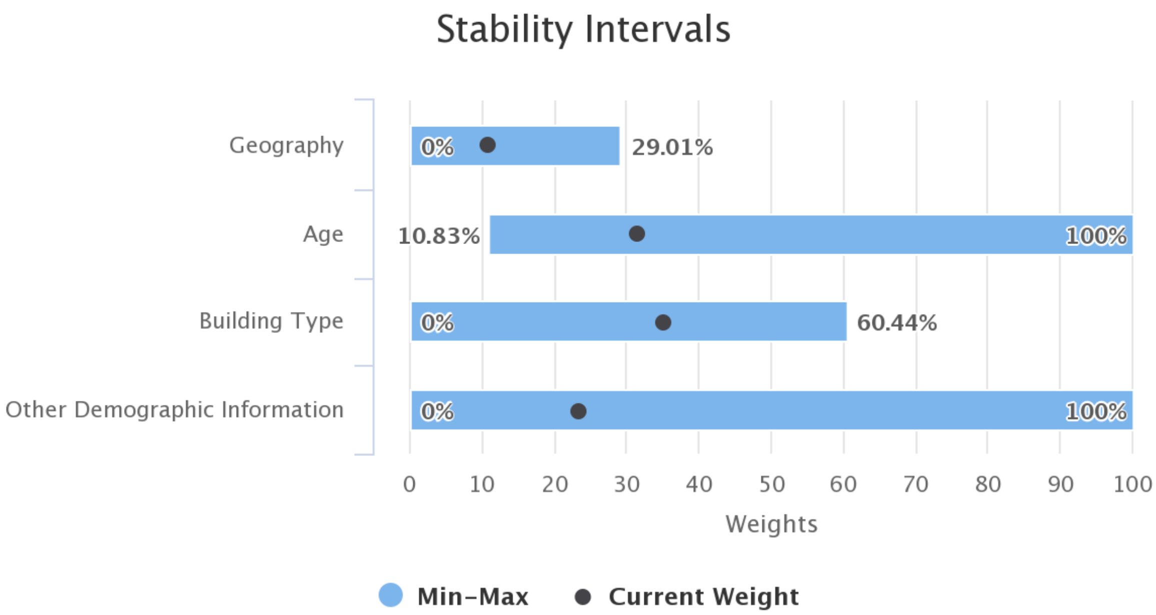

Figure 6: Stability of the categories

But if we compare the category of Age on Figure 6, its weight could not be below 10.83% without changing the ranking. Although, the only category that could have been any weight is the "Other Demographic Information". Thus, the decision maker has a relatively wide freedom of choice about the assignment of the weights.

10 Rank Reversal

We used rank reversal in order to test the validity of our decision. We decided to go beyond the methods mentioned during the class as well as the ones used by our colleauges in the exmaple projects mentioned during the course. The method says that the ranking of alternatives could be affected if an alternative is added or deleted (see wang et al. [18]).

In our case, we erased three alternatives in turn. The first one is the one with the best score (i.e. Rupendehi), the second one is the second one in ranking (i.e. Nawalparasi) and the third one is the fourth in the actual ranking (i.e. Rautahat). Each alternative is then compared to the actual ranking shown in figure 2.

10.0.1 Ranking without Rupandehi

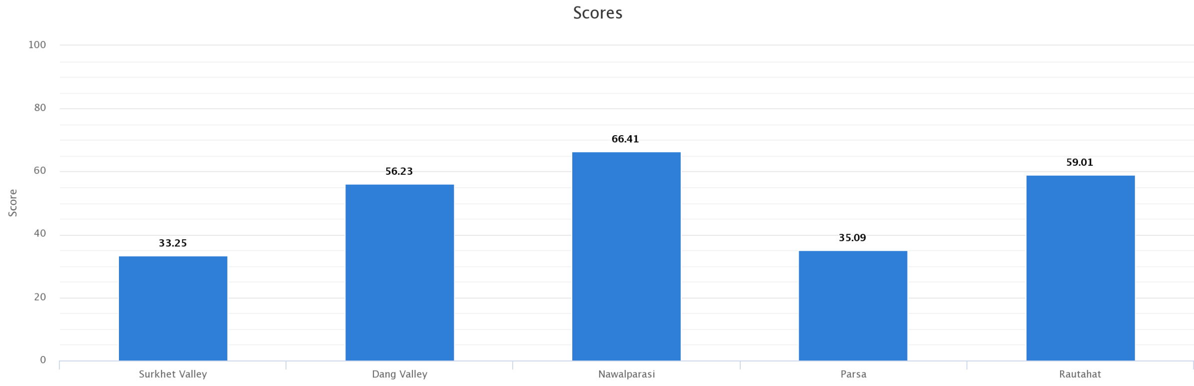

Figure 7: Rank without Rupandehi

	Score Before	Score After
Surkhet Valley	33.27	33.25
Dang Valley	54.75	56.23
Rupandehi	70.12	N/A
Nawalparasi	59.12	66.41
Parsa	30.62	35.09
Rautahat	52.14	59.01

Table 4: Comparative table with and without Rupandehi

By deleting the best alternative, the former number two (i.e. Nawalparasi) takes the top place. But the ranking of all the other alternatives have changed. The model is not stable of this variation.

10.0.2 Ranking without Nawalparasi

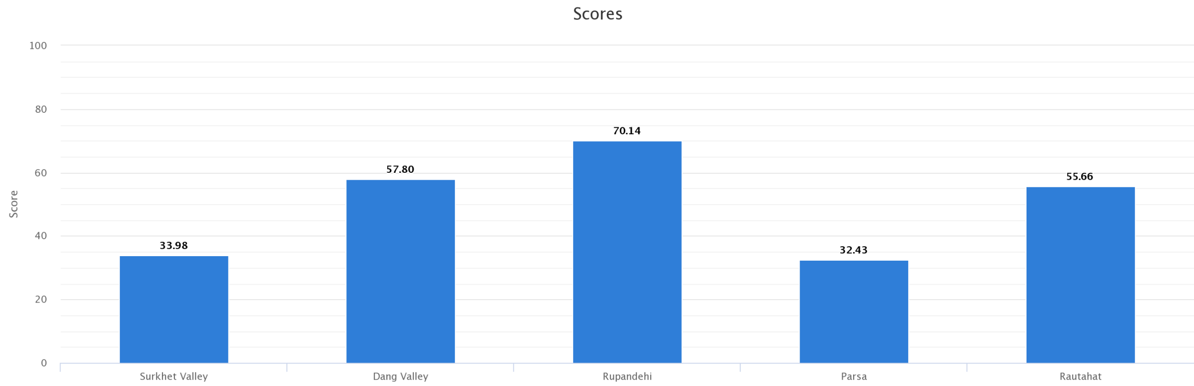

Figure 8: Rank without Nawalparasi

	Score Before	Score After
Surkhet Valley	33.27	33.98
Dang Valley	54.75	57.8
Rupandehi	70.12	70.14
Nawalparasi	59.12	N/A
Parsa	30.62	32.43
Rautahat	52.14	55.66

Table 5: Comparative table with and without Nawalparasi

Under this scenario, the ranking is not modified.

10.0.3 Ranking without Rautahat

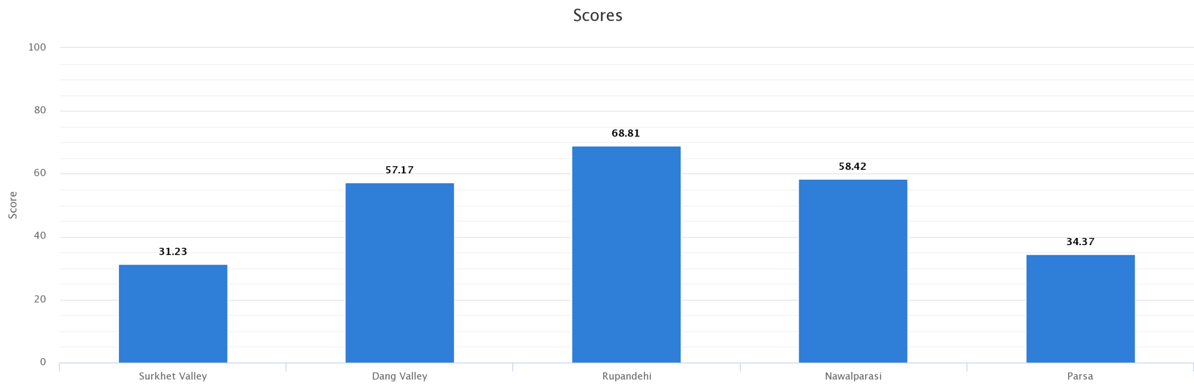

Figure 9: Rank without Rautahat

	Score Before	Score After
Surkhet Valley	33.27	31.23
Dang Valley	54.75	57.17
Rupandehi	70.12	68.81
Nawalparasi	59.12	58.42
Parsa	30.62	34.37
Rautahat	52.14	N/A

Table 6: Comparative table with and without Rautahat

In this case, the ranking of the first three alternative are not vulnerable to this variation. Only the last two (i.e. Surkhet Valley and Parsa) have switch there ranking.

By removing alternatives of the decision making, it can be seen that the robustness of the model is not optimized. It is only valid under certain conditions. However, our best alternatives always remain the same despite the changing of the ranking score.

11 Conclusion

Earthquakes are unpredictable and devastating natural disasters. Sending help,rescues, medical supplies and assistance as effectively as possible could save save the lives of numerous people. Although it is almost impossible to optimize the help at 100%, the Multi Criteria Decision Aid is a powerful tool to make almost objective decisions. This is why the robustness is primordial in the decision. In the case of the Nepal earthquake in 2015, around 9,000 people have lost their lives. This number might have been lower if the supplies had been provided in an optimized way. Thus, the decisions must not be taken lightly.

In this project we offered a proof of concept for prioritisation of rescue mission for a hypothetical earthquake taking place in Nepal. We offered a overall priority table for our alternatives. However, as we mentioned during our analysis section our Pareto-optimal does not include all the alternatives. We left it to the decision maker to select the best and worst alternatives based on their own preferences. The decision maker might change the weights according to some policies set by the governments. For example the decision maker might want to give the building type a different priority and increase the weight age. During our stability analysis we provided a guideline regarding the intervals in which the decision maker can apply their preferred weights for our solution to remain valid. Moreover, our rank reversal test showed that removing alternatives might cause some changes in scores and maybe even the order of alternatives in the ranking table. However the best alternatives remained the same in most cases.

Moreover, our solution is flexibly in the level granularity of the alternatives. A decision maker can always replace our cities with specific regions within a cities or a province. As long as our criteria and categories remain the same our method should apply to different alternatives. The decision maker might need to adjust the thresholds of the preference functions as well the weights for the categories and the criteria according to their own preference should they change the alternatives.

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- Very good model, originality
- very good analysis
- english is weak because many tipos
- good bibliography