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Utilization of Multi-Criteria Decision-Making for Emergency Management

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Abstract. When emergencies or disasters strike, decision-making is a critical component in emergency management. One area of emergency management is ensuring that vulnerable communities are identified and can get the aid they need before, during, and after emergency events. Artificial Intelligence (AI) can be leveraged to improve decision-making in dynamic and complex situations. We propose that Multi-Criteria Decision-Making (MCDM), specifically a hybrid methodology of AHP-TOPSIS, is an approach that can be utilized in AI that can help evaluate, prioritize, and select the most favorable alternative based on computation of the criteria. A study was conducted considering the positive COVID-19 cases in randomly selected counties in three states – Texas, California, and Oklahoma – that have historically experienced the most declared emergencies. The empirical results from the three cases (one case for each state) demonstrate the superiority of the AHP-TOPSIS approach.

Keywords. Multi-criteria decision-making, emergency management, artificial intelligence, social vulnerability index, AHP, TOPSIS.

1 Introduction

Decision-making has a fundamental role in emergency management. An effective approach to emergency management can be broken into four phases: preparedness, response, recovery, and mitigation [1]. In the preparedness phase, emergency plans will be developed. In the response phase, action is taken to save lives and reduce damage. In the recovery phase, efforts to restore the community occur. In in the mitigation phase, policies are put into place to reduce risks to people and property during a disaster. In each of these phases, decision-making is a valuable component.

Over the last several decades, numerous major emergency situations and natural disasters have been recorded. Natural disasters are not just hydro-meteorological (i.e. storms, floods, extreme temperature), but can also be identified as geophysical or epidemiologic [2]. These events can have a significant impact on the well-being of an area's population economically, physically, and psychologically [3]. To make the right decisions that can focus on protecting against the loss of resources or human lives, reliance is given to timely and credible information understanding and reasoning [4].

Artificial Intelligence (AI) techniques and methods have the ability to handle complex big data to learn and be able to make further predictions and classifications. AI is a popular research topic, and has been used in several emergency management applications [3-11]. A goal with implementing AI is to lead towards better decision-making in terms of emergency preparedness, response, recovery, and mitigation. These types of decisions are dynamic, complex, and often have multiple and conflicting criteria and alternatives which require the decision-maker to accurately filter through and prioritize. Multi-Criteria Decision-Making (MCDM) is an approach that can serve as an invaluable tool in decision-making tasks. Alternatives can be evaluated, prioritized, and chosen by using MCDM models [12-14]. Numerous methods have been derived and evolved to accommodate various types of situations and applications [15]. A common method used in research involving complexity is a hybrid method of Analytical Hierarchy Process (AHP) and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS); AHP is used to elicit the criteria weights and TOPSIS is then used to rank the alternatives.

AI certainly has an established place in the domains of both decision support systems and emergency management. As previously mentioned, AI has demonstrated its efficacy with respect to assisting humans in emergency management situations. The complexities involved in providing effective and timely emergency management drive the need for even more assistance to support overwhelmed human decision-makers confronted with a vast array of factors on which to base decisions. These circumstances are well-suited for the application of MCDM models and algorithms in the development of essential decision support systems.

One critical task for which decision support systems can provide aid is the identification of vulnerable areas and communities that may need assistance when emergency events occur. Vulnerabilities can determine individuals who may be more at risk to negative outcomes during emergency situations and natural disasters based on numerous characteristics, including socioeconomic, age, minority status & language, physical environment locations, and health risk concerns. Any method used by emergency management for the purpose of identifying vulnerable communities needs to be able to handle all of the considerations that can influence vulnerability and impact the decisions made, but also be adaptable and dynamic due to the everchanging nature of emergencies.

One tool that is being used to identify vulnerable communities is the Social Vulnerability Index (SVI), which aggregates indicators into a composite score [1, 16]. The index is able to predict which communities are more vulnerable, and help determine where focus should be to distributing help and resources. Issues that may arise with this resource include the simple mathematical computations for a complex issue, and that the criteria that influences vulnerability are not weighted. To address these concerns, we propose using MCDM, specifically AHP-TOPSIS, to help identify vulnerable communities. We hypothesize that the communities that are ranked based on vulnerability will differ due to more sophisticated calculations, and that the AHP-TOPSIS method will produce a more realistic determination.

As a case study to evaluate the proposed methodology, we sought to identify the least and most vulnerable communities in Texas, California, and Oklahoma. These three states are reported to have the most declared emergencies since 1953 [17], and it is important for emergency plans to consider where vulnerable communities exist appropriate actions can be made before, during, and after an emergency or disaster occurs. The methodology’s results, along with the SVI ranks, will be compared with the way counties in the three selected states are ranked based on reported positive COVID-19 cases (COVID-19 being one of the most recent emergencies).

The remainder of this paper is organized in the following four additional sections. Section 2 provides a background on relevant theories and related work. Section 3 provides details of the proposed methodology. Section 4 presents the results and the analysis that was performed; this is followed by a discussion of the results. Concluding remarks are given in Section 5.

2 Theory and Related Works

2.1 Multi-Criteria Decision-Making Algorithms

AHP uses pairwise comparisons and judgments from experts to derive priority measurements. AHP consists of three main parts:

1. decomposing and breaking down the problem into criteria and sub criteria in a hierarchical manner;
2. determining the priorities of the criteria and sub criteria; and
3. synthesizing the priorities to determine which criteria have the highest priority and should be acted upon to influence the problem situation [18-19].

Matrices of pairwise comparisons are formed to estimate the level of importance using numbers from a 1-to-9 AHP fundamental scale. Fundamental Scale: 1-Equal, 3-Moderate, 5-Strong, 7- Very Strong, 9-Extremely Strong, plus numbers in between for intermediate judgments, as well as decimals for finer distinction. A consistency ratio (CR) is then calculated to ensure that the comparison matrix is consistent enough to derive priorities [18-19]. If the CR is significantly small (less than 10%), then the estimate of weight is accepted.

Advantages of AHP include that the method is consistent, flexible, and understandable; sets the problem up into a hierarchical structure; can use quantitative and qualitative criteria; is good for various contexts; and can extend to fuzzy numbers [20-24]. Disadvantages include issues with rank reversal; handling of large quantities of information, uncertainty, and subjectivity; can be computationally complex; and it depends on user preferences [15, 23-25].

Alizadeh et al. (2018) [26] assess seismic vulnerability of residential houses in Tabriz city, Iran using AHP. The results highlighted which areas of Tabriz city exhibited more vulnerability than others, such as the South and Southeast areas. The authors suggest that this method is effective for evaluating seismic vulnerability assessment and could assist urban planners during mitigation and preparatory phases.

Guo and Kapucu (2020) [27] assess social vulnerability to earthquake disasters within Hanzhong city, China using rough AHP. This method allowed the authors to observe the spatial distribution of the social vulnerability.

Ghavami (2019) [28] developed a multi-criteria spatial decision support system (MC-SDSS) that incorporates AHP to evaluate transportation network performance (TNP) in disaster situations.

Tyagi et al. (n.d.) [29] implemented AHP to evaluate the landslide hazard index that is then used to generate landslide hazard zonation. This information was applied to a case study that studied landslide risk for the Tehri area in Uttarakhand, India.

TOPSIS is based on the idea of minimizing the distance or determining the shortest distance from the positive ideal solution and maximizing the distance or determining the farthest distance from the negative ideal solution. The closeness of the alternatives to the ideal solution is evaluated using Euclidean distance [29-30]; by comparing the relative distances, the preference order of the alternatives is determined.

The TOPSIS method is comprised of the following steps [31]:

1. Calculate the normalized decision matrix,
2. Calculate the weighted normalized decision matrix,
3. Determine the positive ideal solution and negative ideal solution,
4. Calculate the separation measures using the n-dimensional Euclidean distance,
5. Calculate the relative closeness to the positive ideal solution, and
6. Rank the preference order.

Some advantages of TOPSIS are that the method is easy to use [32], it is suitable for large-scale data, it provides a solution with precise relative closeness to the positive ideal solution [32, 33], it is simple [15, 33], and it uses a constant number of steps regardless of the number of criteria to consider.

Some disadvantages of TOPSIS are that Euclidean distance does not consider the correlation of criteria [15], judgements are difficult to weight and keep consistent [15], normalization by using vector normalization may be dependent on the evaluation unit of a criterion function [31], problem of rank reversal [34-36], and for the method to work, a maximum and minimum value will need to be identified [34, 37].

Zhang et al. (2019) [38] propose a cyberGIS-enabled MC-SDSS for rapid decision-making in emergency management. The authors produced an application that can provide location information for rescue personnel during disasters to help evacuate people who need help using Twitter data. Geospatial high-performance computing (specifically CyberGIS-Jupyter) is combined with the MCDM methods of weighted sum model (WSM) and TOPSIS to evaluate and identify vulnerable communities in flood emergency situations. In the paper, two objectives test out the proposed method.

Results reveal that WSM generated more diverse values and higher output category estimations than TOPSIS. Overall, WSM and TOPSIS both produced consistent answers for places that have high vulnerability and similar validation results for each decision objective.

Harirchian et al. (2020) [39] use MCDM methods for assessing seismic vulnerability and classify damage index of structures, and then results are validated by the actual damage state observed. From their study, TOPSIS-W1 was determined to contribute the most relevant results in comparison to other tested MCDM methods.

Growing in popularity is the use of a hybrid methodology formed by combining MCDM algorithms together to benefit from the advantages and make up for any disadvantages that a particular algorithm may have. A commonly applied hybrid method is AHP-TOPSIS, especially in complex scenarios. AHP can provide a way of bringing in subjective weights, and TOPSIS will then use those weights in its calculation and ranking of the alternatives.

Wang, Li, Zhang, and Cao (2018) [40] propose a hybrid network architecture for Disaster Area Wireless Networks (DAWNs) for mobility of first responders and refugees. They also propose MCDM emergency communication protocol (ECP) that consists of AHP and TOPSIS for finding an optimal next-hop node in DAWNs.

Ghorui et al. (2021) [41] identified the most dominant risk factor related to the spread of the COVID-19 virus using fuzzy AHP to calculate priority weights and hesitant fuzzy sets with TOPSIS to analyze the most important factor. Results revealed that the most significant risk factor is “long duration of contact with the infected person”.

Jena and Pradhan (2020) [42] proposed to improve earthquake risk assessment in Aceh, Indonesia using a novel combination of artificial neural network cross-validation (fourfold ANN-CV) with hybrid AHP and TOPSIS. This method turned out successful; achieving an accuracy score of 85% and a consistency ratio of 0.06.

2.2 Ranking Comparison

A way to understand the similarity between rankings, several rank evaluation metrics can be used, and in this paper, we describe two metrics: Kendall’s tau rank correlation coefficient (τ_b) and Kendall tau distance.

Kendall’s tau rank correlation coefficient is a non-parametric metric that measures the comparison between ranked data using a value range from 1 to -1, meaning the lists are identical to opposite, respectively [43-45].

Kendall tau distance measures the number of swaps counting the pairwise disagreements between rankings. The distance value can range from 0, indicating a perfect matching ranked list, to the total number of pairs between the lists, indicating completely opposite matching [43].

3 Methodology

3.1 Dataset

The Centers for Disease Control and Prevention Social Vulnerability Index (CDC SVI or SVI) was created by the Agency for Toxic Substances and Disease Registry (ATSDR)’s Geospatial Research, Analysis & Services Program (GRASP) [1 , 16] to help identify communities in the United States that would need support during different stages that a hazardous event occurs. The SVI uses census tract data collected. Fifteen variables are organized into four main theme factors that have an impact on a community’s vulnerability. This includes:

1. socioeconomic status,
2. household composition & disability,
3. minority status & language, and
4. housing type & transportation.

For each alternative, a percentile score is given to each criterion. Percentile scoring ranges from 0-1 or least vulnerable to most vulnerable, respectively. The overall SVI is calculated by summing the four factors, and the four factors have no weights. In this study, the four factors are used as the criteria for the proposed MCDM method.

3.2 Hybrid MCDM Approach

SVI calculations ignore mathematical aggregation across the census factors, with no weighting/implicit weighting involved for any of the factors. This method is simple and straightforward to use, however, it lacks mathematical rigor and focus on the importance of influence that the factors can have on vulnerability. In emergency situations, the goal is that whatever decision that is made will bring the most beneficial ideal solution, and realistic considerations are made in regard to criteria that may impact a community more than others. The benefit of AHP is that it allows for

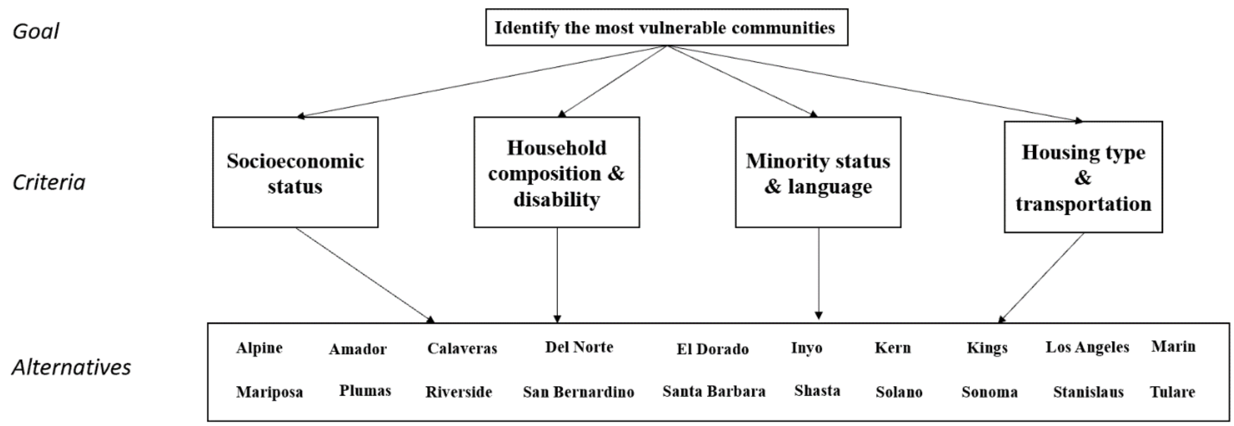

Fig. 1. Hierarchical structure of the problem

judgements of prioritization of the criteria by completing pairwise comparisons; a more thorough perspective than just individual weight assignments on a linear scale. The benefit of TOPSIS is that it will incorporate the positive ideal solution and negative ideal solution into the mathematical computation that will determine the ranks of the alternatives; ensuring that the top choice is the closest to the positive ideal solution and farthest away from the cost.

Even so, it is not realistic to assume that factors in emergency situations have the same weight when it comes to considerations for decisions to be made during emergency planning and aid. For the above reasons, a hybrid MCDM method AHP-TOPSIS is proposed. This will allow for more realistic weights to be applied to the factors, and then those weights will be used in the TOPSIS calculation. Then, the results of the AHP-TOPSIS method can be compared to the SVI calculated vulnerability ranks.

In this study, AHP-TOPSIS is proposed to be used in an emergency management scenario. AHP is used to calculate the weights of the criteria (socioeconomic status, household composition & disability, minority status & language, and housing type & transportation). Preference weights for this case study were determined based on the findings from recent studies [46-47]. The criteria weights that are calculated using AHP are incorporated into TOPSIS, and the alternatives are then ranked. This final ranking highlights the least vulnerable communities to the most vulnerable communities, and then can be compared to the ranks based on COVID-19 cases and SVI ranks.

3.3 Case Study

The proposed method of utilizing AHP-TOPSIS for identifying vulnerable communities was evaluated in a case study using the census information for the US states Texas, California, and Oklahoma.

These states were selected for the purpose of this research as they are reported as the top 3 states for declared emergencies. For each of the three states, the counties are assigned a number, and 20 counties were randomly selected for this preliminary study. Figure 1 depicts the hierarchical structure of the goal, criteria, and alternatives (in this case, for California).

4 Results

The results of using the proposed methodology in the three cases are presented below. Per the above discussion, Kendall's tau correlation and Kendall Distance are used for measuring the comparison between the ranking of counties by COVID-19 positive cases and the two calculated ranks, SVI and AHP-TOPSIS. COVID-19 case-related data as of May 15th, 2021 were used [48].

As a reminder, Kendall's tau can vary from -1 to 1 (higher is better), while the Kendall tau distance can vary from 0 (indicating two perfectly matched

Table 1. Confirmed COVID-19 cases and vulnerability ranks of counties in Texas

County	COVID-19 CASES	SVI	AHP-TOPSIS	County	COVID-19 CASES	SVI	AHP-TOPSIS
Trinity	1	14	6	Pecos	11	17	16
Delta	2	8	4	McLennan	12	15	13
Wood	3	6	5	Hudspeth	13	20	20
Carson	4	1	1	Rockwall	14	2	2
Live Oak	5	12	11	Crane	15	11	15
Terrell	6	9	14	Brown	16	7	3
Brazoria	7	4	10	Chambers	17	3	9
Upton	8	13	17	Burleson	18	10	8
Lynn	9	16	12	Uvalde	19	19	19
Montague	10	5	7	Deaf Smith	20	18	18

Table 2. Confirmed COVID-19 cases and vulnerability ranks of counties in California

County	COVID-19 CASES	SVI	AHP-TOPSIS	County	COVID-19 CASES	SVI	AHP-TOPSIS
Mariposa	1	6	3	Alpine	11	11	7
Plumas	2	4	2	Inyo	12	8	9
Calaveras	3	3	5	Amador	13	7	4
Del Norte	4	17	11	Tulare	14	19	20
El Dorado	5	1	1	Stanislaus	15	14	15
Marin	6	2	8	Riverside	16	12	14
Sonoma	7	5	10	Kern	17	20	19
Shasta	8	10	6	Los Angeles	18	15	17
Solano	9	9	12	San Bernadino	19	13	16
Santa Barbara	10	13	13	Kings	20	18	18

lists) to 190 in our case of having 20 items to rank (190 would indicate the two lists are totally reversed).

4.1 Case #1 - Texas

The results table below (Table 1) highlights three columns of rankings: rankings based on COVID-19 cases, and rankings of vulnerability based on SVI and AHP-TOPSIS calculations. In Column #1 (COVID-19 cases), the counties are ranked from 1–20, 1 representing lowest percentage of confirmed cases in relation to the county's population, and 20 representing the highest percentage. In Columns #2 and #3, the rankings 1 –20 are listed from least vulnerable to most vulnerable in terms the criteria of socioeconomic status, household composition & disability, minority status & language, and housing type & transportation. It is hypothesized that the percentage of counties with confirmed COVID-19 cases is related to its vulnerability (i.e., counties with a low percentage of cases would be those with the least amount of vulnerability).

Table 3. Confirmed COVID-19 cases and vulnerability ranks of counties in Oklahoma

County	COVID-19 CASES	SVI	AHP-TOPSIS	County	COVID-19 CASES	SVI	AHP-TOPSIS
Hughes	1	13	4	Dewey	11	1	2
Okmulgee	2	16	18	Rogers	12	2	7
Haskell	3	19	11	Nowata	13	4	3
Osage	4	5	8	Cherokee	14	20	15
Greer	5	15	10	Kay	15	12	12
Roger Mills	6	3	1	Cotton	16	6	5
Oklahoma	7	10	14	Jackson	17	14	19
Tillman	8	17	13	Carter	18	11	17
Blaine	9	9	9	Beckham	19	7	16
Le Flore	10	18	20	Love	20	8	6

Table 4. Summary of Kendall tau and distance scores for SVI and AHP-TOPSIS methods for each case

	SVI		AHP-TOPSIS	
CASE	**Tau**	**Tau Dist.**	**Tau**	**Tau Dist.**
Case 1 – TX	0.18	78	0.28	68
Case 2 – CA	0.51	47	0.59	39
Case 3 – OK	-0.13	107	0.11	85

Results revealed from both Kendall's tau correlation (τb, where higher is better) and Kendall Distance ("distance", where lower is better) that the ranks from AHP-TOPSIS (τ_b = 0.28; distance of 68) are more similar to the county ranks based on COVID-19 cases than the ranks with SVI (τ_b = 0.18; distance of 78).

Table 1 presents the rankings based on COVID-19 cases, SVI calculation, and AHP-TOPSIS calculation.

4.2 Case #2 - California

Case study #2 resulted with a positive correlation between the ranked counties by COVID-19 cases and the calculated ranks from both SVI and AHP-TOPSIS: cases versus SVI (τ_b = 0.51); and cases versus AHP-TOPSIS (τ_b = 0.59).

With Kendall's Distance, it turned out that the ranking from AHP-TOPSIS was more similar to the reported cases (distance of 39) in comparison to SVI (distance of 47).

Table 2 presents each ranking.

4.3 Case #3 - Oklahoma

The correlation calculations for Case #3 showed that SVI is negatively correlated to the reported cases (τb = -0.13) and AHP-TOPSIS is positively correlated (τb = 0.11).

Likewise with Case #1 and Case #2, AHP-TOPSIS (distance of 85) is confirmed closer in distance to the reported COVID-19 ranks than the SVI ranks (distance of 107).

Table 3 presents each ranking.

5 Conclusions

When emergencies or disasters strike, accurate and timely decision-making is essential for effective emergency management, which consists of preparedness, response, recovery, and mitigation efforts. AI can be leveraged to lead towards improved decision-making in dynamic and complex situations. Often in those situations, conflicting criteria to consider for selecting alternatives can make decision-making a daunting task, and reasoning can be difficult. MCDM is an approach that can help evaluate, prioritize, and select the most favorable alternative based on computation of the criteria.

One area of emergency management is ensuring that vulnerable communities are identified and can get the aid they need before, during, and after emergency events. The Social Vulnerability Index (SVI) is a way to be able to predict the vulnerability of communities based on the main theme factors of socioeconomic status, household composition & disability, minority status & language, and housing type & transportation.

We believe a more sophisticated approach can be taken, in the mathematical computation and weighting of the criteria. With that in mind, we propose using a hybrid algorithm for Multi-Criteria Decision-Making (MCDM), specifically AHP-TOPSIS. We hypothesized that the community vulnerability ranking produced by the SVI would differ from that produced by the AHP-TOPSIS approach, and that the AHP-TOPSIS method would produce a more realistic determination.

As a “proof of concept” with respect to our hypothesis, a study was conducted considering the positive COVID-19 cases in randomly selected counties in three states – Texas, California, and Oklahoma – that have historically experienced the most declared emergencies. The similarity between the ranking of the counties in each state in terms of least to most positive COVID-19 cases and the SVI vulnerability ranking was compared. Then, the positive COVID-19 cases ranking was also compared to a vulnerability ranking produced by the proposed AHP-TOPSIS methodology. Evaluation was complete using metrics of Kendall’s tau rank correlation coefficient and Kendall tau distance. As a reminder, a larger Kendall tau number indicates better correlation between the lists, while a smaller Kendall tau distance indicates better correlation. Table 4 is a summarization of the results.

The empirical results from the three cases (one case for each state) demonstrated the superiority of the AHP-TOPSIS approach. In all comparisons to the ranking based on actual COVID-19 data, the AHP-TOPSIS Kendall tau number was larger (better) than that of the SVI, and the AHP-TOPSIS Kendall tau distance was smaller (better) than that of the SVI. The analysis indicates that while similarities do exist when comparing the methods and at times some ranks match, it is apparent that there are differences and that the ranks are sensitive to criteria weights and rank determination calculations.

The results demonstrate that the proposed methodology of AHP-TOPSIS produces a more realistic vulnerability determination in relation to the ranked percentage of confirmed cases of COVID-19, the most recent large emergency event, in comparison to SVI. With that being said, for future emergency management, it is possible that AHP-TOPSIS would continue to have a better representation than SVI and could be used instead or in conjunction with SVI. While the emergency case study was related to COVID-19, it appears that the hybrid method could be effectively applied to decision-making for other emergency management situations. The alternatives may differ, but the criteria related to vulnerability of communities could potentially still be relevant.

Future work will explore this further, and also evaluate the handling of dynamic aspects of emergent events. In addition, fuzzy set theory will be introduced to generate a dynamic, fuzzy AHP-TOPSIS model.

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