Novel intelligent TOPSIS variant to rank regions for disaster preparedness

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ABSTRACT

An important facet of disaster mitigation is discovering regions based on their lack of preparedness for combating disaster. Accordingly, organizations can lay down appropriate risk management strategies and guidelines to minimize loss due to disaster. "Technique for order of preference by similarity to ideal solution (TOPSIS)" is a popular multi-criteria decision-making (MCDM) method that is deployed for ranking alternatives based on multiple pre-specified criteria. However, the method's efficiency in ranking region as per multiple criteria for disaster management is far from the ground truth. The authors propose a novel intelligent method HCF-TOPSIS, an extension of traditional TOPSIS, to deliver an efficient ranking mechanism for regional safety assessment of disaster affected regions. HCF-TOPSIS capitalizes on entropy (H), closeness (C), and farness (F) metrics to obtain efficient ranking scores of the disaster affected regions. Extensive experimentation validates the claim and proves the superiority of HCF-TOPSIS over existing TOPSIS variants. The proposed research presents many benefits, especially to governments and stakeholders, intending to take appropriate actions to contain disasters.

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1. INTRODUCTION

Natural and man-made disasters pose a significant threat to communities around the world. Their unpredictability adds to the challenge, often leaving affected areas overwhelmed by the scale of the consequences. This can lead to devastating losses in terms of human life, property and environment [1]. Recently, the world was caught unaware of the calamitous COVID-19 pandemic [2]-[4]. The pandemic was termed a disaster as it caused facility closures resulting in shortage of food supplies and jobs; far-reaching physical and mental health issues, and adverse long-term socioeconomic effects [5]-[8]. Governments had to strictly implement containment measures like social distancing and lock-down to avoid the contagion and provide emergency medical aid before a vaccine could be developed to fight the disease [6], [9].

The resulting severe human and economic loss necessitate a strategic planning for combating similar disasters. The intial task is to compute the level of preparedness for all regions by analyzing multiple criteria (possibly conflicting) such as 'emergency preparedness', 'healthcare readiness', 'surveillance capabilities', and so on. Researchers have relied on multiple-criteria decision-making (MCDM) techniques for analysis and strategic decision-making [10], [11]. These techniques rank the regions (alternatives) based on multiple criteria [12], [13], calculate the criteria weights that govern the safety measures [14], [15] and help develop prevention strategies for mitigating the effects of a disaster. Among these, technique for order of preference by similarity to ideal solution (TOPSIS) [12], [16] is commonly used and realistic compensatory method due to its simplicity, comprehensibility, and ease of computation. The method ranks the regions to be monitored by distinguishing between desirable criteria (positive or benefit attributes) and non-desirable criteria (negative or cost attributes) [17], [18]. Between the positive and negative attributes, smaller values are preferred for the negative attributes in comparison to positive attributes. Thus, TOPSIS aims to balance favorable and unfavorable outcomes across multiple criteria. It evaluates alternatives as per the nearness to the ideal solution (maximizing closeness to the best-performing alternative) and farthest distance from the worst solution (minimizing similarity to the worst-performing alternative). This methodology helps identify the most desirable region by considering positive and negative aspects across different criteria [19]-[21].

Effective implementation of TOPSIS is challenging as it depends upon assignment of appropriate weights to the criteria/sub-criteria and use of correct normalization methods. The method also suffers from the rank reversal problem (RRP), which refers to a change in the previously defined ordering among alternatives after inclusion or exclusion of additional alternatives or criteria [22]. As a result, several extensions of TOPSIS have been proposed for aiding strategic decision planning during disaster management [23], [24]. Interested readers can refer to Shih [20] for a comprehensive review of TOPSIS extensions.

TOPSIS extensions have recently been shown to be effective for assessing the impact of COVID-19 and utilizing this information for mitigation of same. These are used for determination of nation-wise regional safety levels and ranking countries using interventional strategies [3], [4], [13], [25], [26]. Recently, Hezer *et al*. [13] applied TOPSIS and other MCDM techniques to rank regions and evaluated the results by comparison with the ground truth findings of the COVID-19 data knowledge group (DKG) report [27]. Even though results were satisfactory, they suggested MCDM-based alternatives leveraging different sub-criteria for better ranking and disaster readiness. The authors introduce "a novel intelligent TOPSIS method, named HCF-TOPSIS", motivated by these issues. This not only overcomes the limitations of traditional TOPSIS by leveraging entropy (H), closeness (C), and farness (F) metrics but also delivers efficient ranking score for the areas when used for assessment of disaster affected regions. The major contributions of this paper are:

- Novel intelligent method HCF-TOPSIS, an extension of traditional TOPSIS, to rank regions according to their disaster readiness.
- Performance comparison of HCF-TOPSIS with a competitive TOPSIS method and the validation of the output ranking using the ground truth available in [27] (subsection 3.2).
- Demonstration of diminishing RRP by HCF-TOPSIS in contrast to a competitive TOPSIS method – H-TOPSIS (subsection 3.3).
- Extensive experimentation to evaluate the efficacy of HCF-TOPSIS considering additional sub-criteria for identifying regions that require special attention (subsection 3.4).

Organization of the paper: section 2 explains the steps of HCF-TOPSIS that ensembles efficient metrics like entropy (H), closeness (C), and farness (F) for ranking regions as per their preparedness to tackle disaster. Section 3 describes the dataset, discusses the results of the experimentation, followed by future scope. Lastly, the conclusion is given in section 4.

2. METHOD

The proposed novel intelligent TOPSIS variant, named as HCF-TOPSIS leverages region ranks to depict performance of a region during disaster. It needs weighted sub-criteria as input along with the decision matrix $[M]$ as shown in (1). It depicts 'm' competitive alternatives $(A_1, A_2, \dots\dots, A_m)$ as rows and 'n' chosen sub-criteria $(SC_1, SC_2, \dots\dots, SC_n)$ as columns.

$$M = \begin{array}{c c} & SC_1 \cdots\cdots\cdots SC_n \\ \begin{array}{c} A_1 \\ \vdots \\ A_m \end{array} & \begin{bmatrix} M_{11} & \dots. & M_{1n} \\ \dots. & M_{ij} & \dots. \\ M_{m1} & \dots\dots & M_{mn} \end{bmatrix} \end{array} \quad (1)$$

Where M_{ij} denotes performance value of j^{th} sub-criterion for i^{th} alternative. Each sub-criterion takes either monotonically increasing or monotonically decreasing performance value. If higher performance value is desirable then the j^{th} sub-criterion is benefit/positive criterion. If lower performance value is desirable, then it is cost/negative sub-criterion. Taking into account the past conduct of regions during disasters, HCF-TOPSIS is used for ranking the regions. Subsection 2.1 details on calculation of weights of sub-criteria, followed by the explanation of the three steps of HCF-TOPSIS (listed below) in subsection 2.2.

- Step I: creation of weighted normalized decision matrix
- Step II: creation of separation vectors
- Step III: ranking of regions

2.1. Obtaining the weights of sub-criteria

Performance of TOPSIS based methods depends on the weights (importance) assigned to sub-criteria. The importance of sub-criteria W= (W_1, W_2, ……, W_n) serve as one of the key factors in ranking the alternatives. Many techniques like equal weights, normalized weights and entropy-based weights have been elaborated in literature to calculate the weights [28]. Literature survey shows that entropy-based weights are superior to equal and normalized weights used in original TOPSIS as they help in extracting information about importance of the sub-criteria [28] and diminish RRP [22]. Therefore, by using entropy metric (H), authors compute weight of sub-criterion j using (2a) to capture its distortion over m regions using (2b). Note that H_j and W_j illustrates the disaster's vulnerability and resilience across all regions depending on sub-criterion j.

$$H_j = -K \sum_{i=1}^{m} \frac{M_{ij}}{\sum_{i=1}^{m} M_{ij}} log \frac{M_{ij}}{\sum_{i=1}^{m} M_{ij}} \tag{2a}$$

$$W_j = \frac{1-H_j}{\sum_{j=1}^{n}(1-H_j)} \tag{2b}$$

Where, $K = \frac{1}{log\ m}$, $0 \leq H_j \leq 1$, $\sum_{j=1}^{n} W_j = 1$.

2.2. Computing ranks for the disaster afflicted areas

For enhanced mitigation of calamity in future, each afflicted area is allocated a rank as per its past performance. The region obtaining higher rank (region with weak performance during past disaster) may be advised to follow the mitigation strategies of region with lower rank (region with good performance during disaster), so as to improve weak region performance in future disaster situation, if any. The ranks are calculated by HCF-TOPSIS using two metrics viz. Closeness (C) and farness (F) which make sure that the rank score (absolute) of the area is nearest to the ideal reference point and farthest from negative ideal reference point respectively. After creation of a weighted normalized decision matrix in step I, separation vectors are obtained in step II. Using absolute distance of closeness to an optimized ideal point (closest to positive ideal solution and farthest from negative ideal solution), step III ranks the regions. Region with the lowest rank is considered as the best region that is least affected by disaster. The details of each step are as follows.

2.2.1. Step I (creation of weighted normalized decision matrix)

Traditional TOPSIS makes use of vector normalization to map each criterion into an equivalent unit for fair comparison. However, researchers have shown that vector normalization aggravates RRP due to dependency among alternatives and use of a fixed ideal solution [22]. Extensive methods have been proposed in literature for normalizing the decision matrix $[M]$ (Table 1). It has been proved that the max method effectively reduces RRP by increasing the range of values of the criteria [22]. Using (3), we apply max-linear normalization on decision matrix $[M]$ to construct normalized decision matrix $[D]$ using user-specified benefit (J^+) and cost (J^-) criteria. In order to capture performance of each area compared to the total performance of the system considering user specified criteria categorization, weighted standardized decision matrix $[V]$ is computed using (4) by multiplying resilience and the performance of each region (i) on sub-criterion (j).

$$if\ j\ \epsilon\ J^+ then\ D_{ij} = \frac{M_{ij}}{M_j^{max}}\ else\ D_{ij} = 1 - \frac{M_{ij}}{M_j^{max}} \tag{3}$$

$$V_{ij} = W_j * D_{ij} \tag{4}$$

2.2.2. Step II (creation of separation vectors)

HCF-TOPSIS method leverages two sets namely hypothetically best (P^+) and worst (P^-) solution set [29] to find the optimal solution which is not only nearest to the best solution, but also the farthest from the worst solution [10]. Observe that $P^+$is a supposed solution having the values of sub-criteria that correspond to positive ideal (best) criteria values in $[V]$. In order to get hypothetical best solution P^+, using (5a), we use the maximum value for the benefit criterion V_j^+ and minimum value for the cost criterion V_j^+ from m alternatives (regions) under study. Similarly, the hypothetical worst solution P^- corresponds to negative ideal (worst) criteria values in $[V]$ where benefit criteria, V_j^- takes the minimum value of the criterion while the cost criteria, V_j^- takes the maximum value of the criterion. P^- for each sub-criterion j is obtained using (5b). Once positive (P^+) and negative (P^-) ideal solutions are in place, separation measures

P_i^+ and P_i^- of each region i are computed using (5c) and (5d) respectively. Euclidean distance has been used for finding separation measures owing to its prevalent use in contrast to rest of the distance measures mentioned in Table 1 [30], [31].

$$P^+ = \{V_1^+, \dots \dots, V_n^+\} \tag{5a}$$

where, $if\ j \in J^+ then\ V_j^+ = max\ (V_{ij})\ else\ V_j^+ = min\ (V_{ij})$

$$P^- = \{V_1^-, \dots \dots, V_n^-\} \tag{5b}$$

where, $if\ j \in J^+ then\ V_j^- = min\ (V_{ij})\ \ else\ \ V_j^- = max\ (V_{ij})$

$$P_i^+ = \sum_j \sqrt{\sum \left(V_{ij} - V_j^+\right)^2} \tag{5c}$$

$$P_i^- = \sum_j \sqrt{\sum \left(V_{ij} - V_j^-\right)^2} \tag{5d}$$

Table 1. Normalization procedures and distance measures used in TOPSIS and its extensions

Normalization procedure/distance measure	Formula
Vector normalization	$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}$,Fiug $i = 1,2,3,4 \dots..m;\ j = 1,2,3,4 \dots..n$
Max linear normalization	$r_{ij} = \frac{x_{ij}}{x_j^*},\ i = 1 \dots m; j = 1 \dots n\ ;\ x_j^* = max_i\{x_{ij}\}$ for benefit criterion; $r_{ij} = \frac{x_j^{\sim}}{x_{ij}},\ i = 1 \dots m;\ j = 1 \dots n\ ;$ $x_j^{\sim} = min_i\{x_{ij}\}$ for cost criterion or $r_{ij} = 1 - \frac{x_{ij}}{x_j^*},\ i = 1 \dots m;\ j = 1 \dots n\ ;\ x_j^* = max_i\{x_{ij}\}$ for cost attributes
Max-min linear Normalization	$r_{ij} = \frac{x_{ij} - x_j^{\sim}}{x_j^* - x_j^{\sim}}$ for benefit attributes and $r_{ij} = \frac{x_j^* - x_{ij}}{x_j^* - x_j^{\sim}}$ for cost attributes
Sum linear normalization	$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}}}$, $i = 1,2,3,4 \dots..m;\ j = 1,2,3,4 \dots..n$
Minkowski's metric	$L_p(x,y) = \{\sum_{j=1}^{n} \lvert x_j - y_j \rvert^p\}^{1/p}$, where $P \geq 1$ and with n dimensions (i) Manhattan (city block) distance $p = 1$; (ii) Euclidean distance $p = 2$; (iii) Tchebycheff distance $p = \infty$
Weighted metric	$L_p(x,y) = \{(w_j \sum_{j=1}^{n} \lvert x_j - y_j \rvert)^p\}^{1/p}$, where $P \in \{1,2,3, \dots\}$ U $\{\infty\}$; wj is the weight on the jth dimension or direction. The distance names are defined in the same way as above (i)– (iii).

2.2.3. Step III (ranking of regions)

Traditional TOPSIS calculates the relative closeness coefficient to positive ideal solution set by choosing the region that has the closest distance value from the positive-ideal solution and the farthest distance from the negative-ideal solution to get ranks [22]. Subsequently, regions are sorted in descending order on the rank scores to report alternatives with higher scores as more effective in combating disaster in comparison to the other regions. Relative distance measure is a popular method to find an ideal solution [32]. However, using it leads to changing of ideal points when alternatives are either added or removed resulting in RRP. Use of absolute distance measures keeps RRP under control [32]. Using relative distance measure, computations of positive and negative ideal solutions result in non-uniformities in rankings given by TOPSIS [29]. Normalization procedure which uses absolute terms reduces RRP as it allows the alternatives to remain independent to some extent Talukdar and Dutta [29]. tackles RRP by considering the TOPSIS value of alternatives based on absolute closeness to positive and negative ideal solution [33].

Instead of calculating relative closeness to positive ideal solution, an ideal reference point is used in HCF-TOPSIS to get absolute closeness to positive ideal solution (C_i^+) and absolute farness from negative ideal solution (F_i^-) for each region i using (6a) and (6b) respectively. Let $O\left(C_P, F_N\right)$ be an optimized ideal reference point where $C_P = \min\ (P^+)$ and $F_N = \max\ (P^-)$. Simply stated the reference point is closest to the positive ideal solution and farthest from the negative ideal solution. Here, the closeness (C) metric is used to calculate absolute closeness to positive ideal solution and farness (F) metric is used to calculate absolute farness from negative ideal solution for each region. HCF-TOPSIS calculates absolute Euclidean distance between each region i and an ideal reference point to get its score S_i using (6c). The Euclidean distance ensures absolute HCF-TOPSIS score (S_i) instead of relative score in traditional TOPSIS. Lesser the score S_i

given by TOPSIS, closer is C_i^+ to point O and farther is F_i^- to point O. Thus, it ranks the regions as per the increasing order of S_i. In case two or more regions get the same score, then only closeness to positive ideal solution is considered for ranking giving weightage to benefit criteria.

$$C_i^+ = P_i^+ - C_P \tag{6a}$$

$$F_i^- = P_i^- - F_N \tag{6b}$$

$$S_i = \sqrt{[C_i^+]^2 + [F_i^{-2}]} \tag{6c}$$

3. RESULTS AND DISCUSSION

This section strives to establish the efficacy of the novel HCF-TOPSIS method in ranking COVID-19 affected regions as per their safety and preparedness. Code written using Python 3 is executed on Intel(R) Core (TM) i7, CPU @1.80 GHz having 16 GB RAM. We have utilized the datasets and the ranks available in the report [27] for the experimentation. We have used entropy-based variation of TOPSIS (H-TOPSIS) as a competitive method in the experiments as it is more efficient over traditional TOPSIS for ranking COVID-19 affected regions [4], [25], [28].

3.1. Data description

In 2020, data analysis of about 200 regions for COVID-19 safety ranking and risk assessment was performed to provide a framework [21], [27]. It grouped 200 countries into four levels with level 1 countries having the highest safety score and level 4 having the lowest safety score. The ranking was obtained using six benefit-oriented criteria (Table 2), which in turn comprises of a total of 34 sub-criteria. The report emphasizes on close monitoring of all the six criteria to analyze regions influenced by disaster to control its severity. We have used regional DKG scores as ground truth for result comparison [27].

Table 2. Standard benefit criteria used in DKG report [27]

Criteria	Sub-criteria
Quarantine efficiency	Scale and timeline of quarantine, criminal penalties for violating quarantine, economic support for quarantined citizens, economic and supply chain freezing, travel restrictions
Government efficiency of risk management	Level of security and defense advancement, rapid emergency mobilization, efficiency of government structure, economic sustainability, legislative efficiency, political stability
Monitoring and detection	Monitoring systems, disaster management, scope of diagnostic methods, testing efficiency, AI for diagnostics and prognostics, govt surveillance tech for monitoring, reliability of data
Emergency preparedness	Societal emergency resilience, emergency military mobilization exp., surveillance capabilities, previous national emergency experience
Healthcare readiness	COVID equipment availability, mobilization of healthcare resources, quantity and quality of medical staff, healthcare progressiveness and tech advancement, epidemiology system level of development
Regional resilience	Infection spread risk, culture specifics and societal discipline, level of modern sanitization methods, demography, chronic diseases, societal risks

3.2. Validating performance of HCF-TOPSIS using six standard criteria

Using the proposed HCF-TOPSIS and H-TOPSIS method, region scores have been calculated for level 1, 2 and 3 using six standard positive criteria from the report [27]. Normalized scores obtained by two methods along with DKG region scores are shown in Figures 1(a) to (c) for three different levels respectively. It is evident that in almost all the regions, HCF-TOPSIS score is closer to DKG score values in contrast to those given by H-TOPSIS for all three levels. This means the HCF-TOPSIS method is better than H-TOPSIS. To establish the soundness of HCF-TOPSIS, Spearman’s rank correlation coefficients is computed for which scores are ranked from 1 to N starting from highest value where N signifies number of regions observed for safety preparedness. Table 3 shows the Spearman’s rank correlation coefficient between DKG ranks and that obtained from HCF-TOPSIS and H-TOPSIS methods respectively for all levels (1, 2, 3). The values confirm that HCF-TOPSIS scores are closer to the ranks depicted in DKG report than those generated by the H-TOPSIS method. Computation of means absolute error (MAE) and Root Mean Squared error (RMSE) is done to find the errors in scores calculated by HCF-TOPSIS and H-TOPSIS methods in order to compare with the DKG scores.

For the three levels, Figures 2(a) to (c) compare the MAE and RMSE of the two methods. Lesser error values for HCF-TOPSIS compared to H-TOPSIS at all levels demonstrate the ability of HCF-TOPSIS in producing scores near to DKG scores. Thus, the hybrid HCF-TOPSIS is a superior version of TOPSIS to rank the regions influenced by disaster.

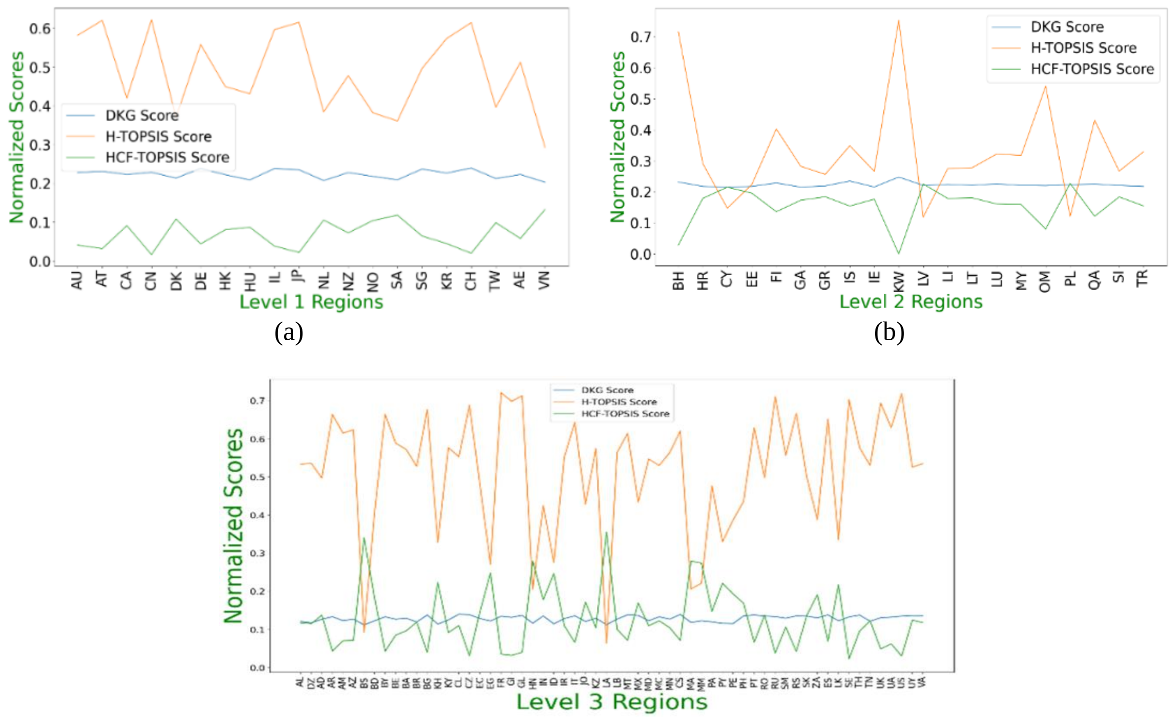
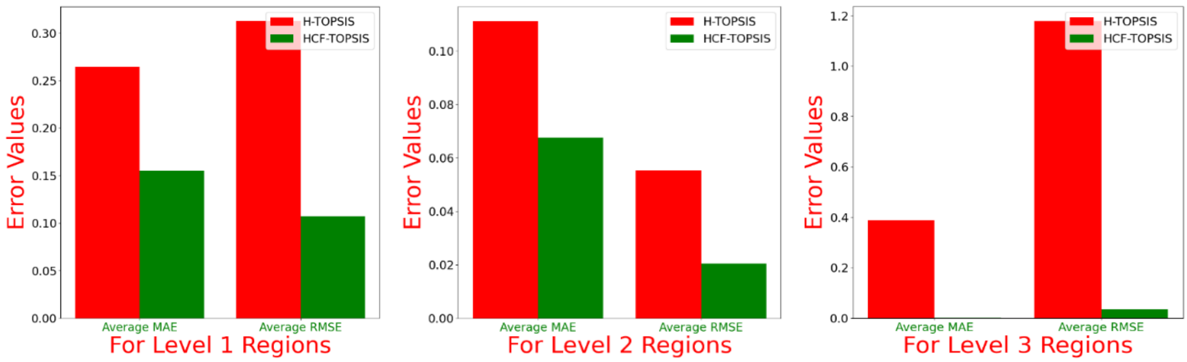


Figure 1. Comparison of HCF-TOPSIS, H-TOPSIS and DKG report using normalized scores for regions at various levels: (a) regions at level 1, (b) regions at level 2, and (c) regions at level 3

Table 3. Spearman's rank correlation of DKG ranks at 3 levels

Level	H-TOPSIS	HCF-TOPSIS
Level 1	0.831579	0.866165
Level 2	0.545865	0.563759
Level 3	0.625674	0.644837



(a) (b) (c)

Figure 2. Efficacy comparision of HCF-TOPSIS and H-TOPSIS using means absolute error and root mean square error for regions at various levels: (a) regions at level 1, (b) regions at level 2, and (c) regions at level 3

3.3. RRP mitigation evaluation using HCF-TOPSIS

We also observed the capability of HCF-TOPSIS method to tackle the rank reversal problem (RRP). In earlier studies, it is reported that RRP is more affected by changing the number of alternatives [31], [32]. Hence, we initially considered top-10 regions of level 1 and computed the MAE for comparative evaluation of HCF-TOPSIS and H-TOPSIS with respect to DKG scores. Then, we considered top 15 regions and recomputed the MAE. The results shown in Table 4 shows a considerable reduction in MAE in the case of HCF-TOPSIS with the addition of alternatives whereas there was little change in case of H-TOPSIS. This shows the efficiency of HCF-TOPSIS in mitigating the RRP.

Table 4. MAE reported by H-TOPSIS and HCF-TOPSIS with varying alternatives at level 1

# Alternatives (at level 1)	H-TOPSIS	HCF-TOPSIS
Top-10	0.17	0.15
Top-15	0.18	0.11

3.4. Performance evaluation of HCF-TOPSIS using sub-criteria

A recent paper by Hezer *et al.* [13] suggests that ranks can be refined for the regions by including sub-criteria from the report [27]. Close monitoring of criteria of areas influenced by disaster enables governments to prepare judicious plans to contain severity of disasters. Considering this, we select 34 sub-criteria for level 1 regions only as done in DKG report. We also differentiate between benefit and cost sub-criteria instead of considering all as positive criteria as used by Hezer *et al.* [13]. Out of 34 sub-criteria, 19 were considered as benefit and rest 15 were taken as cost according to their semantics discussed below. Here, (+) symbol signifies that the authors have considered the sub-criterion as benefit, whereas (−) symbol signifies cost sub-criterion.

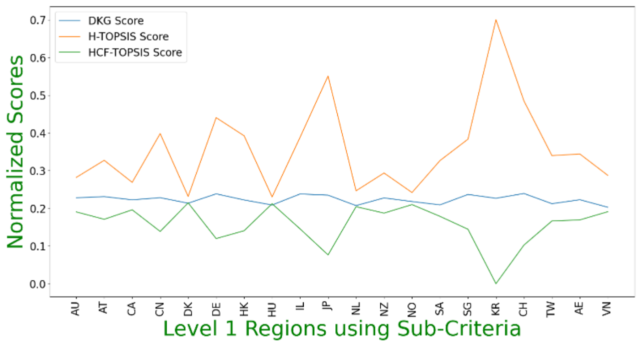
Countries measure geopolitical vulnerabilities (+) by checking their political strength keeping in mind military stoutness, they also measure economic sustainability (+) based on growth rate of its debt and capability to be financially stable and sustainable in post pandemic era. Both these sub-criteria directly impact the way in which risk knowledge is gained. The sub-criterion previous national emergency experience (+) takes into account the policies made and relief efforts undertaken by government in the past. Societal emergency resilience (+) also considers past history and judge’s attitudes, preparedness and resilience of the population. Together these two helps in identifying existing/new risk factors. Further, the sub-criterion chronic diseases (−) assesses geographic risk by identifying highly populated regions within the country, number of bordering regions and infection-prone areas in vicinity of the country. Infection spread risk (−) determines what part of population is medically or otherwise unfit and is likely to catch infection. Level of modern sanitization methods (+) used and COVID-19 equipment availability (+) determine the readiness of the country to face any pandemic. Epidemiology system level of development (+) performs medical research on spread, distribution and control of disease. All these criteria help in identifying high risk factors.

Government’s legislative efficiency (+) for deploying emergency response legislation in response to any hazard/pandemic and its rapid emergency mobilization (−), that is, its capability to organize emergency response, play a significant part in warning the communities ahead of the impending danger. Emergency military mobilization experience (−) takes into account past exposure of preparing military for national emergencies and uses it to effectively combat current pandemic by disseminating information about it to general public. Further, efficiency of government structure (+) and sophistication of surveillance capabilities (+) play major part in identifying risk-prone regions and warning such regions at the earliest.

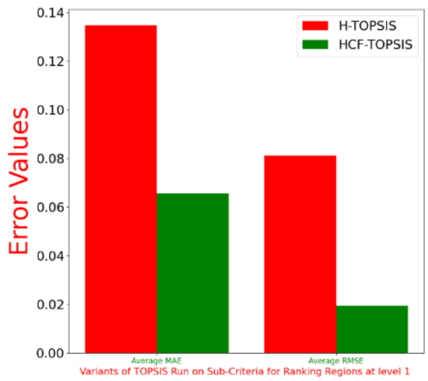
The sub-criteria monitoring systems and disaster management (+) and government surveillance technology for monitoring (+) assess the diverseness and level of sophistication and widespread use of monitoring and surveillance technologies in a country. Later also keeps track of infection rate and adherence to social spacing and quarantine norms. After monitoring comes diagnostics which is affected by sub-criteria: reliability and transparency of data (+) which takes into account reliability of country’s reported statistics related to infection, hospitalization and mortality; scope of diagnostic methods (+) determines diversity of specific diagnostic techniques used in a country and their effectiveness; AI for diagnostics and prognostics (+) helps in analyzing COVID results via artificial intelligence methods thereby reducing the need for manpower to do the same work. To decide quarantine measures for a country scale of quarantine (−) determines whether lockdown is required or social distancing will achieve the purpose of controlling the spread of disease. Quarantine timeline (−) determines when to initiate quarantine measures.

The first response of a government towards controlling the spread of a pandemic is economic and supply chain freezing (−) via lockdown and strictly implementing travel restrictions (−). Economic support for quarantine citizens (−) from the government is also of paramount importance which would support them through the crisis. Further, criminal penalties for violating quarantine (−) dictates the existence and extremity of criminal punishments for breaching the quarantine rules of a region. Mobilization of new healthcare resources (−) which includes readiness to organize extra healthcare resources of a region, helps communities respond to the pandemic in a better way. Response is also governed by quantity and quality of medical staff (−), level of healthcare progressiveness (+), level of technological advancement (+), that is, sophistication/modernization/efficacy of healthcare network and testing efficiency (−) determined by testing schedule, accessibility of laboratory staff. Culture specifics and societal discipline (−) also makes a huge difference to response capability as it determines whether cultural practices are focused not only on sanitization but also on health. Demography (−) sub-criteria points towards vulnerable demographics in any regions of a country. These vulnerable categories of people may not respond. And last important sub-criterion is Level of security and defense advancement (+) to counterbalance outside threats. It does contribute towards response capability as security only allows governments to use other response measure mentioned above during pandemic.

We compare performance of HCF-TOPSIS and H-TOPSIS considering all sub-criteria with DKG scores of level 1 regions (Figure 3(a)). The graph demonstrates that HCF-TOPSIS scores are analogous to DKG scores in comparison to H-TOPSIS scores. It establishes confidence in using refined sub-criteria for the safety evaluation of regions and validating the efficacy of the HCF-TOPSIS method for the same. Further, we also calculate errors (RMSE, MAE) for the computed ranks for the regions at level 1 (Figure 3(b)). Low errors by HCF-TOPSIS compared to H-TOPSIS proves its usability in ranking regions on safety sub-criteria. Also, errors have reduced by including refined criteria for level 1 compared to errors reported using six standard criteria (Figure 1(a)) for both methods. Thus, using refined sub-criteria improves the ranking of regions for managing natural disasters and their preparedness. Authors report results for the regions of level 1 only, as the sub-criteria values were missing in the DKG report for the regions at level 2 and level 3. Further, on comparing HCF-TOPSIS for ranking the regions of level 1 using 6 standard benefit criteria with that using 19 benefit and 15 cost sub-criteria, we observe better ranks for the latter case (see Table 5). Hence, we conclude that novel intelligent HCF-TOPSIS delivers better ranking of regions influenced by disaster when run on sub-criteria instead of criteria.



(a)



(b)

Figure 3. Comparison of HCF-TOPSIS, H-TOPSIS and DKG report using sub-criteria for regions at level 1: (a) normalised scores and (b) error values (average mae and average rmse)

Table 5. Errors reported by HCF-TOPSIS for regions at level 1

Technique	Average MAE	Average RMSE
HCF-TOPSIS on 6 Benefit Criteria	0.154	0.107
HCF-TOPSIS on 34 Sub-Criteria	0.065	0.019

3.5. Future scope

Machine learning (ML) is a branch of AI that helps the systems to learn and improve from experience with minimal human intervention and helps make better decisions [33]. MCDM using ML is important because of presence of large number of conflicting criteria and multiple alternatives. Also, it is challenging to work with multiple alternatives as the complexity of assigning numbers (importance) to the criteria according to their preference increases. In future, the authors intend to apply different ML algorithms (viz. supervised, unsupervised, semi-supervised, and reinforcement learning algorithms) on available data to build the decision matrix that is a pre-requisite for applying the TOPSIS method.

4. CONCLUSION

COVID-19 brought the entire world population to its knees in 2020. To better equip the stakeholders to fight such disasters, it is crucial to identify regions that exhibited lower levels of readiness in the past. The authors have proposed HCF-TOPSIS, a novel intelligent MCDM technique with the intention of ranking the affected areas depending on their performance in combating disasters. It makes use of sub-criteria weights using entropy (H). The aim is to identify regions that are both closest (C) to the positive ideal solution and farthest (F) from the negative ideal solution. Experiments conducted have shown that HCF-TOPSIS is more effective than H-TOPSIS, a variant of traditional TOPSIS. This ranking system can help policymakers develop more effective strategic plans to combat future pandemics. The authors intend to use machine learning algorithms in future to extract decision matrices from COVID-19 data, construct groups of sub-criteria and apply intelligent HCF-TOPSIS to get realistic rankings of the regions. This will assist the government organizations in making more informed decisions.

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