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A new emergency response of spherical intelligent fuzzy decision process to diagnose of COVID19

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Abstract

The control of spreading of COVID-19 in emergency situation the entire world is a \mathfrak{c}' allege, and therefore, the aim of this study was to propose a spherical intelligent fuzzy decision model for control and "agnosis COVID-19. The emergency event is known to have aspects of short time and data, harmfulness, and ambiguity and policy makers are often rationally bounded under uncertainty and threat. There are some classic approaches for representing and explaining the complexity and vagueness of the information. The effective tool to describe and reduce the uncertainty in data information is fuzzy set and their extension. Therefore, we used fuzzy logic to develop fuzzy mathematical model for control of transmission and spreading of COVID19. The fuzzy control of early transmission and spreading of coronavirus by fuzzy mathematical model will be very effective. The proposed research work is on fuzz_y mathematical model of intelligent decision systems under the spherical fuzzy information. In the proposed work, we will develop a newly and generalized technique for COVID19 based on the technique for order of preference by similarity to α . If so ution (TOPSIS) and complex proportional assessment (COPRAS) methods under spherical fuzzy environment. Finally an illustrative the emergency situation of COVID-19 is given for demonstrating the effectiveness of the suggested method, along with a sensitivity analysis and comparative analysis, showing the feasibility and reliability of its results. **Process to diagnose of COVID19**
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Keywords Spherical fuzzy set · Intelligent accision support systems · Emergency decision making of COVID-19 · Critical path problems

1 Introduction

The situation of the world for the people is very risky to spend the peaceful life due to the spreading of the COVID-19. The COVID-1^{\circ} viral distribution and the world health organization (VHO) declared an emergency situation due the spreading COVID-19. In the end of 2019, some cases **r** order as same symptoms in the Wuhan city,

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province Hubei, China, after the diagnosing of these cases reported as novel coronavirus (COVID-19). This deadly virus has infected the entire world and many people have died as a result of this insuperable virus. The name "coronavirus" comes from the Latin word "corona" which means a "crown, circle of light or nimbus". This virus influences immediately to your lungs. It has comparable symptoms as influenza and pneumonia. In the beginning, various of those infected worked or shopped at a wholesale seafood market in Wuhan, China. After that it radiates universally through import, export, travelling and social contacting of infected people. The Fig. 1 represents the world wide confirmed cases till May 4, 2020.

Several researchers investigated and developed different methods for addressing obstacles to medical and decisionmaking. In practical decision making, there are a great quantity of uncertainties, imprecise and vague information, whose representations and managements are always the central issues. Health professionals and healthcare administrators are working to reduce clinical and maintenance costs for the prevention and management of corona dis-

Fig. 1 COVID-19 confirmed cases distribution

ease. Expenditure and need for health care are both growing fast. Health care practitioners, administrators and other sectors collectively perform a range of healthcare management techniques with the goal of facilitating effective disease $r_{\rm{eff}}$ vention approaches using scarce resources. Such principles are used to build a decision-making model using a number of parameters and alternatives (Cromwell et a^1 , $\sqrt{915}$). The purpose of the multiple criteria decision $m_1k_1n_2$ (CDM) frameworks is to prepared an appropriate decisions at different levels of health care, such as oper tional, n ethodical, and functional. There may be an ideal solution to any difficult decision-making problem, but μ difficult task to find such a method. In particular, management accisions are taken by managers or senior management to grow and maintain the organization. In fact, there contradictions in strategic decisions, possible synergies between different options, and uncertainty in the final result. When strategic decisions are taken, the company shall agree on tactical and operational planning decisions. Strategic, tactical, and operational planning are grouped together as a taxonomy of health planning (K_umar et al. 2017). Disease prevention and control approvas include multiple management roles like as facility preparation, organization and decision making.

MCDM problems with spherical fuzzy environment took much attention to the real-life problems where the goal is associated for selecting the best alternative in contrast to the nite values under the different criteria where the evaluation terms are SFNs given by decision experts (DEs). However, in order to process the ambiguity /imprecision in the data, theories like as fuzzy set (FS) (Zade[h](#page-16-0) [1965](#page-16-0)), intuitionistic FS (IFS) (Attanasso[v](#page-15-2) [1986](#page-15-2)), picture FS (Cuong and Kreinovic[h](#page-15-3) [2013\)](#page-15-3), spherical FS (Ashraf and Abdulla[h](#page-15-4) [2019\)](#page-15-4), are applied widely. Presently, decision-making is a hot topic in the field $\overline{}$ rearch which includes the following three main steps:

- Zo describe the information, collect the data on an appropriate scale.
- (b) Obtain the totally preference value of the object by assigning the various attribute values.
- (c) Rank the objects in a transparent process to get the suitable alternative(s).

Therefore, the intention of the present research is to describe a group decision making method to resolve the multicriteria group decision making (MCGDM) problems for SFSs with robust generalized TOPSIS-COPRAS approach based on the spherical fuzzy information. The novelty of fuzzy set firstly defined by Zadeh (1965) to use non-statistical and vague phenomena. Since the inception, the theory of FS became a more interesting research area, e.g., image processing, data mining, engineering, medical sciences, clustering, statistical information theory and information technology. Since FSs assign only a crisp membership function of an element to show the double conflicting states, one is support and other is disagree. Thus, fuzzy set theory faces the limitation to show the negative state. To avoid this limitation, Atanassov (Attanasso[v](#page-15-2) [1986\)](#page-15-2) developed the idea of intuitionistic fuzzy sets (IFSs) theory based on the notion of fuzzy set (FS) by Zadeh. The application of IFSs have investigated by many authors (Mendel et al[.](#page-15-5) [2019a,](#page-15-5) [b](#page-15-6); Mende[l](#page-16-1) [2019b](#page-16-1)). Atanassov Atanasso[v](#page-15-7) [\(2018a,](#page-15-7) [b](#page-15-8), [2015\)](#page-15-9) presented the dfferent decision making techniques to tackle the uncertainty in real life decision making problems. Sotirov et al[.](#page-16-2) [\(2018\)](#page-16-2) introduced the hybrid approach for modular neural network

design using intercriteria analysis and intuitionistic fuzzy logic. Sotirov et al[.](#page-16-3) [\(2016\)](#page-16-3); Castillo et al[.](#page-16-4) [\(2015\)](#page-16-4) proposed the novel modular neural network preprocessing procedure with intuitionistic fuzzy intercriteria analysis method to tackle the uncertainty in real life DMPs. Although, IFS based models have been successfully implemented in different areas since its appearance, but there are practical situations in real-world which cannot be represented by the traditional IFSs. Recently, (Cuong and Kreinovich 2013) filled these gaps by introducing the neutral membership in Atanassov's IFS theory. Picture fuzzy set (PFS) in a finite fixed set \Re is written as $\{(\partial_\gamma, P_\flat(\partial_\gamma), I_\flat(\partial_\gamma), N_\flat(\partial_\gamma)) | \partial_\gamma \in \Re\}$ where $P_{\rm b}$, $I_{\rm b}$, $N_{\rm b} \in [0, 1]$ with condition that $0 \leq P_{\rm b} + I_{\rm b} + I_{\rm c}$ $N_{\rm b} \leq 1$. Basically, PFSs can precisely describe a human views, including more responses, such as: "yes", "abstain", "no" and "refusal". Many researcher (Ashraf et al. 2019e, f; Khan et al. 2019a, b, c; Wei 2017; Zeng et al. 2019) contributed to the picture FS. Since the introduction of IFS, the theories and applications of IFS have been studied comprehensively, including its' applications in DMPs. These researches are very appropriate to tackle DMPs under PFS environment only owing to the condition $0 \le P_1 + I_1 + N_2 \le$ 1. However, in practical DMPs, the decision makers provides evaluation value in the form of $(P_{\text{b}}, I_{\text{b}}, N_{\text{b}})$, but it may be not satisfy the condition $0 \le P_{\rm b} + I_{\rm b} + N_{\rm b} \le 1$ and beyond the upper bound 1. Aiming at this limitation which Pr_{max} can not handle, (Ashraf and Abdullah 2019) established a new concept of spherical fuzzy (SF) set to handle y ith this situaltion. SFS is an extension of PFS by slackening the condition $0 \le P_b^2 + I_b^2 + N_b^2 \le 1$. We must also *i* bte that the acceptable spherical fuzzy space increases, the providing more freedom for observers to express their belief in supporting membership. Therefore, SFSs exp. ess . extensive fuzzy information; Whilst, SFSs are more maneuverable and more appropriate for dealing with uncertainties information. Several researchers have done quite valuable contributions in the expansion of $5.$ set and its approach to different fields, their results shows the great success of SF set in theoretical and tec^l nical aspects. As aggregation operators have a strong role play n decision-making problems (DMPs), sever_{al} search τ have done quite valuable contributions to in ⁴ $\frac{1}{2}$ $\frac{$ gation operators based on algebraic norms (Ashraf et al. $2019a$) cealing with uncertainty and inaccurate information in DMPs. SF set the representation of SF norms (Ashraf et al[.](#page-15-16) [2019b\)](#page-15-16) and TOPSIS methodology introduced for SF information. SF Dombi aggregation operators based on Dombi norm are introduced in Ashraf et al[.](#page-15-17) [\(2019c](#page-15-17)). SF Logarithmic aggregation operators based on entropy are proposed in Jin et al[.](#page-15-18) [\(2019a](#page-15-18)). Linguistic SF aggregation operators are presented in Jin et al[.](#page-15-19) [\(2019b](#page-15-19)) for SF information to tackle the uncertainty in DMPs. Ca[o](#page-15-20) [\(2019\)](#page-15-20) proposed the spherical linguistic Muirhead mean operators and discussed Is have been successfully implementation different areas are inclusive fit AB[R](#page-15-15)/3 (1933) to determine the state of the

their application in group DMP. GRA methodology based on spherical linguistic fuzzy Choquet integral is proposed (Ashraf et al[.](#page-15-21) [2018](#page-15-21)) for SF information. Cosine similarity measures are presented in Rafiq et al[.](#page-16-7) [\(2019\)](#page-16-7) to discussed the application in DMPs. Application of SF distance measures are discussed in Ashraf et al. $(2019d)$ to determined the child development influence environmental f ctors using SF information. In Zeng et al. (2019) proposed the TOP-SIS approach based on SF rough Set and discussed their application in DMPs. Gündoğdu et al. (20b) presented the TOPSIS methodology using $5F$ information and discussed their real life application **n** DMPs. Gündoğdu and Kahraman $(2020c)$ introduce the Δ FD method and also presented its application to the linear delta robot technology development problem. Gündo gdu (2020a); Gündoğdu and Kahraman (2019) exted the concept of spherical fuzzy set to interval-yalued fuzzy set and presented the decision making method ¹0₀, tackle in uncertainty in DMPs. Khan et al. $(2020a)$ introduced the distance and similarity measures *n* spherical fuzzy sets and discussed their applications in selecting mega projects. Ashraf et al. $(2020g)$ proposed the symmetric sum based aggregation operators for herical fuzzy information and discussed their application in multi-attribute group decision-making problem. Ashraf et al. (2020h) presented the decision making technique using sine function and Barukab (Barukab et al[.](#page-15-30) 2019) introduced new approach to fuzzy TOPSIS method based on entropy measure under spherical fuzzy information.

Just like these DM methods, we have the most fruitful method called TOPSIS method, which was introduced in 1981, by Hwang and Yoon (1981). The abbreviation, TOP-SIS stands for "technique for order preference by similarity to the ideal solution. This method was developed later by many authors. The high flexibility of the TOPSIS concept allows us to add additional extensions to make the best choices in different situations. Practically, TOPSIS and its modifications are used to solve many theoretical and real-world problems (Boran et al. 2009; Chen 2000; Nag and Helal 2016; Wang and Elhag 2006; Wang et al. 2018). In complex decision making, where the results can be easily evaluated by using TOPSIS method, contains a lot of qualitative information. The decision makers have limited attention and information processing skills. The TOPSIS method is a practical and useful technique for ranking and selection of alternatives.

Complex Proportional Assessment (COPRAS) (Zavadskas and Kaklauska[s](#page-16-12) [1996](#page-16-12)) methodology proposed by Zavadskas and Kaklauskas in 1996, which is most effectively and commonly used technique to deal with the uncertainty in DMPs. It is used to evaluate alternatives dependent on several criteria by applying the corresponding weights of parameters and the degree of usefulness of alternatives.

Choosing the appropriate alternative is achieved by focusing at the ideal and anti-ideal solutions. COPRAS claims that the importance and usefulness features under investigation are directly and proportionately dependent on a set of criteria that describes alternatives efficiently and on the criteria's values and weights. COPRAS has many benefits, such as less processing time, a very easy and straightforward method of computing etc, over other MCDM methods such as EVAMIX, VIKOR and AHP.

With respect to the advantages of SF set in describing uncertain information, also, regardless of the motivation and inspiration of all the above debate, we enlist the main objectives of the article:

- 1) Article main objective to provides a new strategy to SF set through emergency group decision making problem (GDMP) for control and prevent the COVID-19 effectively.
- 2) In this paper, a new methodology based on TOPSIS approach hybrid with the COPRAS, which can deal much more uncertainties in the form of spherical fuzzy sets. Note that, in comparisons with the classic fuzzy sets, spherical fuzzy set has more capability to deal the different situations more successfully. In fact, the sets consider opinions of DMs better than classic $f(x)$ zy That is why, to use advantages and flexibility of the S_F sets, the introduced technique is established under these sets to discourse the uncertainty of real-life in bette way. First is values and weights. COPRAS has many benefits and where $P_2(\beta_1) P_3 = 0$

LEVAMIX, VIKOR and AHR

BENAMIX, VIKOR and AHR

BENAMIX, VIKOR and AHR

DEVAMIX, VIKOR and AHR

DEVAMIX, VIKOR and AHR

DEVAMIX, VIKOR and
- 3) We design an algorithm to tackle e ergency decisionmaking problem of COVID-19.
- 4) We shall collect the exact μ disaster during the COVD-19 and then construct h_{ℓ} m nematical model of emergency decision support vstems for COVD-19 under generalized structure of spherical fuzzy sets and compare our propose techniques ique with existing techniques to shows the validity and effectiveness of the proposed methodo $\log y$.

achieve the list of goals the structure of the paper is arranged as follows: In Sect. 2, some basic concepts are introduced. In Sect. 3, proposed the different types of distance between SF numbers. Section [4,](#page-4-1) gave the main contribution of the paper, introduced the TOPSIS-COPRAS technique to deal with the uncertainty in DMP using SF information. Section [5,](#page-6-0) propose the numerical case study of outbreak of coronavirus as an emergency decision support problem to demonstrate the applicability and reliability of the proposed technique. Section [6](#page-10-0) presents the comparison analysis to shows the applicability of the proposed methodology and concluded remarks are discussed in Sect. [7.](#page-12-0)

2 Preliminaries

In this section, for better understanding of the spherical fuzzy sets, some related basic concepts will be briefly reviewed.

Definition 1 Zade[h](#page-16-0) [\(1965\)](#page-16-0) A fuzzy set ε in fixed set \Re is described as

$$
\varepsilon = \left\{ \left\langle \partial_{\gamma}, P_{\flat} \left(\partial_{\gamma} \right) \right\rangle | \partial_{\gamma} \in \mathfrak{R} \right\},\
$$

where $P_{\text{b}}(\partial_{\gamma}) \in [0, 1]$ called positive membership grade.

By $\varepsilon_1 \subseteq \varepsilon_2$ we mean that P_{b_1} λ $\leq P_{b_2}(\partial_\gamma)$ for each $\partial_{\gamma} \in \mathfrak{R}$. Clearly $\varepsilon_1 = \varepsilon_2$ if $\varepsilon_1 \leq \varepsilon_2$ and $\varepsilon_2 \subseteq \varepsilon_1$.

Utilizing (Zadeh 195), proposed min-max system to define basic operation ι l laws as follows:

(1)
$$
\varepsilon_1 \cap \varepsilon_2 = \{\text{im } P_1(\lambda_y), P_{b_2}(\lambda_y)\} | \partial_y \in \mathbb{R} \},
$$

\n(2) $\varepsilon_1 \cup \varepsilon_2 = \{\text{m } P_{b_1}(\lambda_y), P_{b_2}(\lambda_y)\} | \partial_y \in \mathbb{R} \},$
\n(3) $\varepsilon_1^c = P_{b_1}(\lambda_y) | \partial_y \in \mathbb{R} \},$
\nwhere $\varepsilon_1, \varepsilon_2 \in F\hat{S}(\mathbb{R})$ and $\partial_y \in \mathbb{R}$.

Definition 2 (Ashraf and Abdullah 2019)A spherical fuzzy set ε in fixed set \Re is described as

$$
s = \left\{ \left\langle \partial_{\gamma}, P_{\flat} \left(\partial_{\gamma} \right), I_{\flat} \left(\partial_{\gamma} \right), N_{\flat} \left(\partial_{\gamma} \right) \right\rangle | \partial_{\gamma} \in \mathfrak{R} \right\},
$$

where $P_{\text{b}}(\partial_{\gamma}) \in [0, 1]$ positive membership, $I_{\text{b}}(\partial_{\gamma}) \in [0, 1]$ neutral membership and N_b (∂_γ) \in [0, 1] negative membership grades, respectively. In addition, it is necessary to $0 \le P_\flat^2(\partial_\gamma) + I_\flat^2(\partial_\gamma) + N_\flat^2(\partial_\gamma) \le 1$, for each $\partial_\gamma \in \Re$.

To what follows, we symbolize the collection of all spherical fuzzy sets in \Re by $\hat{S}F\hat{S}(\Re)$. For convenience, the spherical fuzzy number (SFN) is symbolized by the triplet $\varepsilon = (P_{\text{b}}, I_{\text{b}}, N_{\text{b}})$.

Let $\varepsilon_1, \varepsilon_2 \in \hat{S} \in \hat{S}(\Re)$. Ashraf and Abdullah (2019) defined the following notions:

(1) $\varepsilon_1 \subseteq \varepsilon_2 \iff \text{if } P_{\mathfrak{b}_1}(\partial_\gamma) \le P_{\mathfrak{b}_2}(\partial_\gamma), I_{\mathfrak{b}_1}(\partial_\gamma) \le$ $I_{\flat_2}(\partial_\gamma)$ and $N_{\flat_1}(\partial_\gamma) \ge N_{\flat_2}(\partial_\gamma)$ for each $\partial_\gamma \in \mathfrak{R}$. Clearly $\varepsilon_1 = \varepsilon_2$ if $\varepsilon_1 \sqsubseteq \varepsilon_2$ and $\varepsilon_2 \sqsubseteq \varepsilon_1$.

$$
(2) \varepsilon_{1} \sqcap \varepsilon_{2} = \left\{ \frac{\min (P_{b_{1}} (\partial_{\gamma}), P_{b_{2}} (\partial_{\gamma})), \min (I_{b_{1}} (\partial_{\gamma}), I_{b_{2}} (\partial_{\gamma})),}{\max (N_{b_{1}} (\partial_{\gamma}), N_{b_{2}} (\partial_{\gamma}))) |\partial_{\gamma} \in \mathfrak{R}} \right\},
$$

$$
(3) \varepsilon_{1} \sqcup \varepsilon_{2} = \left\{ \frac{\max (P_{b_{1}}(\partial_{\gamma}), P_{b_{2}}(\partial_{\gamma})), \min (I_{b_{1}}(\partial_{\gamma}), I_{b_{2}}(\partial_{\gamma})), I_{b_{2}}(\partial_{\gamma})), \, I_{b_{2}}(\partial_{\gamma})), \, I_{b_{2}}(\partial_{\gamma} \right\},\,
$$

(4)
$$
\varepsilon_1^c = \{ N_{b_1} (\partial_\gamma), I_{b_1} (\partial_\gamma), P_{b_1} (\partial_\gamma) | \partial_\gamma \in \mathbb{R} \},
$$

where $\varepsilon_1, \varepsilon_2 \in \hat{S} \cap \hat{S}(\mathbb{R})$ and $\partial_\gamma \in \mathbb{R}$.

Definition 3 (As[h](#page-15-4)raf and Abdullah [2019\)](#page-15-4)Let $\varepsilon_1 = \left\{ P_{\mathfrak{b}_1} \left(\partial_{\gamma} \right), \right\}$ $I_{\flat_1}(\partial_\gamma)$, $N_{\flat_1}(\partial_\gamma)$ } and $\varepsilon_2 = \{P_{\flat_2}(\partial_\gamma)$, $I_{\flat_2}(\partial_\gamma)$, $N_{\flat_2}(\partial_\gamma)\}$ \in $\hat{S}FN$ (\Re) with $\varpi > 0$. Then, the operational rules are as follows:

$$
(1) \varepsilon_{1} \otimes \varepsilon_{2} = \left\{ P_{b_{1}} P_{b_{2}}, I_{b_{1}} I_{b_{2}}, \sqrt{N_{b_{1}}^{2} + N_{b_{2}}^{2} - N_{b_{1}}^{2} N_{b_{2}}^{2}} \right\};
$$
\n
$$
(2) \varepsilon_{1} \oplus \varepsilon_{2} = \left\{ \sqrt{P_{b_{1}}^{2} + P_{b_{2}}^{2} - P_{b_{1}}^{2} P_{b_{2}}^{2}}, I_{b_{1}} I_{b_{2}}, N_{b_{1}} N_{b_{2}} \right\};
$$
\n
$$
(3) \varepsilon_{1}^{\varpi} = \left\{ (P_{b_{1}})^{\varpi}, (I_{b_{1}})^{\varpi}, \sqrt{1 - (1 - N_{b_{1}}^{2})^{\varpi}} \right\};
$$
\n
$$
(4) \varpi \cdot \varepsilon_{1} = \left\{ \sqrt{1 - (1 - P_{b_{1}}^{2})^{\varpi}}, (I_{b_{1}})^{\varpi}, (N_{b_{1}})^{\varpi} \right\}.
$$

Definition 4 Ashraf et al. (2019a)Let $\varepsilon_k = \{P_{\nu_k}(\partial_\gamma),\}$ $\left\{ I_{b_{k}}\left(\partial_{\gamma}\right), N_{b_{k}}\left(\partial_{\gamma}\right) \right\} \in \hat{S}FN$ (H) and $SFWA$: $SFN^{n} \rightarrow$ *SFN* be a mapping defined as

$$
SFWA\left(\varepsilon_1,\varepsilon_2,\ldots,\varepsilon_n\right)=\sum_{k=1}^n\tau_k\varepsilon_k.
$$

Then, by operational laws of SFNs, we obtained spherical fuzzy weighted averaging operator as

$$
SFWA (\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_n)
$$

=
$$
\left\{ \sqrt{1 - \Pi_{k=1}^n (1 - P_{\nu_k}^2)^{\tau_k}}, \Pi_{k=1}^n (I_{\nu_k})^{\tau_k}, \right\}.
$$

 $\sum_{k=1}^{n} \tau_k = 1$ is $\tau = {\tau_1, \tau_2, ..., \tau_n}.$ where the weight vector of $\varepsilon_k (k \in N)$ with $\tau_k \geq 0$ and

Definition 5 Ashraf et al. (2019a) Let ε_k = $\mathcal{F}_{p_k}(\partial_\gamma)$ $\left\{I_{b_k}\left(\partial_\gamma\right), N_{b_k}\left(\partial_\gamma\right)\right\} \in \hat{S} \cap N \left(\Re\right) \text{ and } SFWG \in \mathbb{R}^{N^2} \rightarrow \mathbb{R}$ *SFN* be a mapping defined as

$$
SFWG(\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_n) = \prod_{k=1}^n \varepsilon_k^{\tau_k}
$$

Then, by operational laws \sim SFNs, we obtained spherical fuzzy weighted geometric operator

$$
SFWG(\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_n) = \begin{cases} \Gamma_{k=1}(P_{b_k})^{\tau_k}, \Pi_{k=1}^n(I_{b_k})^{\tau_k}, \\ \sqrt{1 - \Pi_{k=1}^n (1 - N_{b_k}^2)^{\tau_k}} \end{cases}.
$$

 \sum Where the weight vector of $\varepsilon_k (k \in N)$ with $\tau_k \geq 0$ and $\sum_{i=1}^{n} \tau_k = 1$ is $i = {\tau_1, \tau_2, ..., \tau_n}$. $= {\tau_1, \tau_2, \ldots, \tau_n}.$

3 Distance of spherical fuzzy sets

Definition 6 Let $\varepsilon_1 = \{P_{b_1}(\partial_\gamma), I_{b_1}(\partial_\gamma), N_{b_1}(\partial_\gamma)\}\)$ and $\varepsilon_2 = \{ P_{\mathfrak{b}_2}(\partial_\gamma), I_{\mathfrak{b}_2}(\partial_\gamma), N_{\mathfrak{b}_2}(\partial_\gamma) \} \in \hat{S}FN \times \mathfrak{B}.$ Then maximum distance $d_{\text{Max}}(\varepsilon_1, \varepsilon_2)$ is defined as

$$
d_{\text{Max}}(\varepsilon_1, \varepsilon_2) = \frac{1}{n} \sum_{p=1}^n \max \left(\left\{ \begin{matrix} |P_{b_1}(\partial_{\gamma_p}) - P_{b_2}(\partial_{\gamma_p})| + \\ |I_{b_1}(\partial_{\gamma_p}) - I_{b_2}(\partial_{\gamma_p})| + \\ |N_{b_1}(\partial_{\gamma_p}) - N_{b_2}(\partial_{\gamma_p})| \end{matrix} \right\} \right).
$$

Definition 7 Let $\varepsilon_1 = \{P_{b_1}(\partial_\gamma), I_{b_1}(\partial_\gamma), N_{b_1}(\partial_\gamma)\}\$ and $\varepsilon_2 = \{ P_{\flat_2} (\partial_\gamma) , I_{\flat_2} (\partial_\gamma) , N_{\flat_2} (\partial_\gamma) \} \in \hat{S} \in N(\Re)$. Then minimum distance $d_{\text{Min}}(\varepsilon_1, \varepsilon_2)$ is defined as

$$
d_{\text{Min}}(\varepsilon_1, \varepsilon_2) = \frac{1}{n} \sum_{p=1}^n \min \left(\left\{ \begin{array}{l} \left| P_{b_1} \left(\partial_{\gamma_p} \right) - P_{b_2} \left(\partial_{\gamma_p} \right) \right| + \\ \left| I_{b_1} \left(\partial_{\gamma_p} \right) - I_{b_2} \left(\partial_{\gamma_p} \right) \right| + \\ \left| N_{b_1} \left(\partial_{\gamma_p} \right) - N_{b_1} \left(\partial_{\gamma_p} \right) \right| \end{array} \right) \right).
$$

Definition 8 Let $\varepsilon_1 = \{P_{b_1}(\partial_\gamma), I_{b_1}(\partial_\gamma), N_{b_1}(\partial_\gamma)\}$ and $\varepsilon_2 = \{P_{b_2}(\partial_\gamma), I_{b_2}(\partial_\gamma), N_{b_2}(\partial_\gamma)\}\in N(G)$). Then Hamming distance $d_{HD}(\varepsilon_1, \varepsilon_2)$ is *defined as*

$$
d_{HD}(\varepsilon_1, \varepsilon_2) = \frac{1}{n} \sum_{p=1}^n \left(\left\{ \frac{|P_{\cdot_1}(\partial_{\gamma_p}) - P_{\cdot_2}(\partial_{\gamma_p})| +}{|N_{b_1}(\partial_{\gamma_p}) - N_{b_2}(\partial_{\gamma_p})| +} \right\} \right).
$$

Definition 9 Let ε_1 $\{P_{\flat_1}(\delta_\gamma)$, $I_{\flat_1}(\partial_\gamma)$, $N_{\flat_1}(\partial_\gamma)\}$ and $\varepsilon_2 = \left\{ P_{\mathfrak{b}_2}(\partial_\gamma) \middle| \right\} \subset \hat{S} \subset \hat{$ Euclidean distance α $\beta(\varepsilon_1, \varepsilon_2)$ is defined as

$$
\mathcal{E}_1, \mathcal{E}_2) = \sqrt{\frac{1}{n} \sum_{p=1}^n \left(\frac{(P_{b_1}(\partial_{\gamma_p}) - P_{b_2}(\partial_{\gamma_p}))^2}{(I_{b_1}(\partial_{\gamma_p}) - I_{b_2}(\partial_{\gamma_p}))^2 + (N_{b_1}(\partial_{\gamma_p}) - N_{b_2}(\partial_{\gamma_p}))^2} \right)}.
$$

De inition 10 Let $\varepsilon_1 = \{P_{b_1}(\partial_\gamma), I_{b_1}(\partial_\gamma), N_{b_1}(\partial_\gamma)\}\$ and $\varepsilon_2 = \{P_{b_2}(\partial_\gamma), I_{b_2}(\partial_\gamma), N_{b_2}(\partial_\gamma)\}\in \hat{S}FN \text{ (}\mathfrak{R}\text{)}.$ Then normalized Hamming distance $d_{NHD}(\varepsilon_1, \varepsilon_2)$ is defined as

$$
d_{NHD}(\varepsilon_1, \varepsilon_2) = \frac{1}{2n} \sum_{p=1}^n \left(\left\{ \begin{array}{l} |P_{b_1}(\partial_{\gamma_p}) - P_{b_2}(\partial_{\gamma_p})|+ \\ |I_{b_1}(\partial_{\gamma_p}) - I_{b_2}(\partial_{\gamma_p})|+ \\ |N_{b_1}(\partial_{\gamma_p}) - N_{b_2}(\partial_{\gamma_p})| \end{array} \right\} \right).
$$

Definition 11 Let $\varepsilon_1 = \{P_{b_1}(\partial_\gamma), I_{b_1}(\partial_\gamma), N_{b_1}(\partial_\gamma)\}\$ and $\varepsilon_2 = \{P_{b_2}(\partial_\gamma), I_{b_2}(\partial_\gamma), N_{b_2}(\partial_\gamma)\}\in \hat{S}FN$ (\Re). Then normalized Euclidean distance $d_{NED}(\varepsilon_1, \varepsilon_2)$ is defined as

$$
\begin{aligned}\n\text{A in } \mathcal{F}(k) > \mathcal{F} \cdot \mathcal{E}_1 = \left\{ \sqrt{1 - (1 - P_{\alpha_1}^2)^{(0)}}, \quad (\beta_1)^m, (\beta_2)^m \right\}.\n\end{aligned}
$$
\n
$$
\begin{aligned}\n\text{A in } (\mathcal{E}_1, \mathcal{E}_2) > \mathcal{E}_1 \cdot (\beta_1) \cdot \beta_2 \cdot (\beta_1) \cdot \beta_3 \cdot (\beta_2) \\
\text{A in } (\mathcal{E}_1, \mathcal{E}_2) > \mathcal{E}_1 \cdot (\beta_2) \cdot \beta_3 \cdot (\beta_3) \\
\text{A in } (\mathcal{E}_1, \mathcal{E}_2) > \mathcal{E}_2 \cdot (\beta_2) \cdot \beta_3 \cdot (\beta_3) \\
\text{B in } (\mathcal{E}_1, \mathcal{E}_2) > \mathcal{E}_2 \cdot (\beta_1) \cdot \beta_2 \cdot (\beta_2) \cdot (\beta_3) \cdot (\beta_2) \\
\text{B in } (\mathcal{E}_2, \mathcal{E}_2) > \mathcal{E}_2 \cdot (\beta_1) \cdot (\beta_2) \cdot (\beta_3) \cdot (\beta_2) \\
\text{B in } (\mathcal{E}_1, \mathcal{E}_2) > \mathcal{E}_2 \cdot (\beta_1) \cdot (\beta_2) \cdot (\beta_2) \cdot (\beta_3) \\
\text{B in } (\mathcal{E}_1, \mathcal{E}_2) > \mathcal{E}_2 \cdot (\beta_1) \cdot (\beta_2) \cdot (\beta_2) \cdot (\beta_2) \cdot (\beta_2) \\
\text{B in } (\mathcal{E}_1, \mathcal{E}_2) > \mathcal{E}_2 \cdot (\beta_1) \cdot (\beta_2) \cdot (\beta_1) \cdot (\beta_2) \\
\text{B in } (\mathcal{E}_1, \mathcal{E}_2) > \mathcal{E}_2 \cdot (\beta_1) \cdot (\beta_2) \cdot (\beta_1) \cdot (\beta_2) \\
\text{B in } (\mathcal{E}_1, \mathcal{E}_2) > \mathcal{E}_2 \cdot (\beta_1) \cdot (\beta_1) \cdot (\beta_1) \cdot (\beta_1) \cdot (\beta_1) \cdot (\beta_1) \\
\text{B in } (\mathcal{E}_1, \mathcal{E}_2) > \mathcal
$$

4 Proposed methodology

In this segment, we proposed the methodology to deal with uncertainty and inaccurate information in the form of SFSs in DMPs. The proposed methodology has following steps:

Step-1 Data Collection

Judgements of specialists' decision maker (DM) experts on assessments criteria for every activity and each criterion weights are assembled in the shape of initial decision matrixes. At primary, the D_k matrix

constructed on ideas of kth DM is computed as below:

$$
[D_k]_{\alpha\gamma} = \begin{array}{c} \text{activity 1} \\ \vdots \\ \text{activity } p \end{array} \begin{bmatrix} \varepsilon_{11}^k & \cdots & \varepsilon_{1j}^k \\ \vdots & \ddots & \vdots \\ \varepsilon_{p1}^k & \cdots & \varepsilon_{pj}^k \end{bmatrix} \qquad (4.1)
$$

where, $1 \le \alpha \le p$ denotes the activities, $1 \le \gamma \le j$ denotes the criteria, respectively, and $1 \leq k \leq m$ represents the specialists' decision makers. Then, the D_k spherical fuzzy matrix constructed on ideas of kth DM is computed as follows:

$$
[D_k]_{\beta\gamma} = \begin{array}{c} \text{activity 1} \\ \vdots \\ \text{activity q} \end{array} \begin{bmatrix} \varepsilon_{11}^k & \cdots & \varepsilon_{1j}^k \\ \vdots & \ddots & \vdots \\ \varepsilon_{q1}^k & \cdots & \varepsilon_{qj}^k \end{bmatrix} \tag{4.2}
$$

where, $1 \leq \beta \leq q$ denotes the numbers of paths (alternatives).

Step-2 Calculation Of DMs Weights

- Each specialists' decision maker give specified weight to decision matrix. In this step, we calculate the weights of the decision matrices by utilizing the closeness to average ideal solution and maximum distance from positive and negative ideal solutions.
- **Step-2(a)** In this step, utilizing (Yue 2011) methodology find the average D^* , left negative $\overline{L}D$ and right negative *RD*[−] ideal solutions as **follows**

$$
D^* = \varepsilon_{\beta\gamma}^* = \begin{bmatrix} \varepsilon_{11}^* & \cdots & \varepsilon_{1j}^* \\ \vdots & \ddots & \vdots \\ \varepsilon_{q1}^* & \cdots & \varepsilon_{qj}^* \end{bmatrix}
$$
(4.3)
where $\varepsilon_{\beta\gamma}^*$

$$
\frac{1}{m} \sum_{k=1}^m N_{\beta\gamma} \quad \text{with } 1 \le \beta \le q \text{ and } 1 \le \gamma \le j.
$$

$$
D^- = \beta_{\gamma} = \begin{bmatrix} \varepsilon_{11}^{l-} & \cdots & \varepsilon_{1j}^{l-} \\ \vdots & \ddots & \vdots \\ \varepsilon_{q1}^{l-} & \cdots & \varepsilon_{qj}^{l-} \end{bmatrix}
$$
(4.4)
where $\varepsilon_{\beta\gamma}^{l-} = \min_{1 \le k \le t} (\varepsilon_{\beta\gamma}^k)$

where
$$
\varepsilon_{\beta\gamma} = \min_{1 \le k \le t} \left(\varepsilon_{\beta\gamma}^{\varepsilon} \right)
$$

\n
$$
= \left(\min_{1 \le k \le t} P_{\beta\gamma}^{(k)}, \min_{1 \le k \le t} I_{\beta\gamma}^{(k)},
$$

\n
$$
\min_{1 \le k \le t} N_{\beta\gamma}^{(k)} \right) \text{ with } 1 \le \beta \le q \text{ and } 1 \le \gamma \le j.
$$

$$
RD^{-} = \varepsilon_{\beta\gamma}^{R-} = \begin{bmatrix} \varepsilon_{11}^{R-} & \cdots & \varepsilon_{1j}^{R-} \\ \vdots & \ddots & \vdots \\ \varepsilon_{q1}^{R-} & \cdots & \varepsilon_{qj}^{R-} \end{bmatrix}
$$
 (4.5)

where
$$
\varepsilon_{\beta\gamma}^{R-} = \max_{1 \le k \le t} \left(\varepsilon_{\beta\gamma}^k \right)
$$

\n
$$
= \left(\max_{1 \le k \le t} P_{\beta\gamma}^{(k)}, \max_{1 \le k \le t} I_{\beta\gamma}^{(k)}, \max_{1 \le k \le t} I_{\beta\gamma}^{(k)}, \max_{1 \le k \le t} I_{\beta\gamma}^{(k)} \right)
$$

\n
$$
\max_{1 \le k \le t} N_{\beta\gamma}^{(k)} \left(\min_{1 \le k \le t} \beta \right) = \varepsilon
$$

Step-2(b) To measure decision level of each DM, we find the distance between each individual decision matrix D_k ($1 \leq k \leq m$) with average ideal matrix *D*[∗], left negative ideal solution *LD*[−] and rⁱght negative ideal solution *RD*[−]. Consider that the Euclidean distance is the most widely used tool to measure the separation of two objects in practical applications, we utiliz it to *easure the sepa*ration between L_k with LD^- and RD^- as follows.

activity
$$
p \left[\begin{array}{c} \varepsilon_{p1}^{k} \cdots \varepsilon_{pj}^{k} \end{array} \right]
$$
 the distance between each individual
denotes the criteria, respectively, and $1 \le k \le m$
denotes the criteria, respectively, and $1 \le k \le m$
represents the special size of ision makes. Then, the
D_k spherical size is decision makes. Then, the
expression is especially its decision makes. Then, the
activity $1 \left[\begin{array}{c} \varepsilon_{11}^{k} \cdots \varepsilon_{1j}^{k} \\ \vdots \vdots \ddots \vdots \\ \varepsilon_{q1}^{k} \end{array} \right]$ (4.2)
the *D L*

Step-2(c) Proposed the final closedness coefficient value of each DM is calculated as

$$
FCV^{(k)} = SM_k^- + \frac{\sum_{k=1}^{m} SM_k}{SM_k \sum_{k=1}^{m} \frac{1}{SM_k}}
$$
(4.8)

where SM_k^- = max $\left\{ SM_k^{l-}, SM_k^{R-} \right\}$ **Step-2(d)** Final weights ν_k of each DM is obtained as

$$
b_k = \frac{FCV^{(k)}}{\sum_{k=1}^{m} FCV^{(k)}}
$$
(4.9)

Step-3 Aggregated matrix is obtained by using spherical fuzzy weighted averaging operator

 $SFWA(\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_n)$

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$$
= \left\{ \sqrt{1 - \Pi_{k=1}^{n} (1 - P_{b_k}^2)^{\tau_k}}, \Pi_{k=1}^{n} (I_{b_k})^{\tau_k}, \atop \Pi_{k=1}^{n} (N_{b_k})^{\tau_k} \right\}
$$
(4.10)

Step-4 Aggregated spherical matrix for all the possible paths is constructed by using the addition rules of spherical fuzzy set as follows

$$
(\varepsilon_1 \oplus \varepsilon_2 \oplus \cdots \oplus \varepsilon_n) = \left\{ \begin{pmatrix} P_{\flat_1}^2 + P_{\flat_2}^2 + \cdots + P_{\flat_n}^2 - \\ \left(P_{\flat_1}^2 P_{\flat_2}^2 \cdots P_{\flat_n}^2 \right) \\ I_{\flat_1} I_{\flat_2} \cdots I_{\flat_n} , N_{\flat_1} N_{\flat_2} \cdots N_{\flat_n} \end{pmatrix}^{\frac{1}{n}}, \right\}
$$

Step-5 Positive ideal $(\rho_{\beta\gamma}^+)$ and negative ideal $(\rho_{\beta\gamma}^-)$ solutions are calculated as

$$
\rho_{\beta\gamma}^{+} = \left\{ v_{\gamma}^{+} \middle| \left(\max_{\gamma} \left(P_{\beta\gamma} \right), \min_{\gamma} \left(I_{\beta\gamma} \right), \min_{\gamma} \left(N_{\beta\gamma} \right) \right) \right\} \tag{4.11}
$$

$$
\frac{\text{and}}{\rho_{\beta\gamma}} = \left\{ v_{\gamma}^{-} \mid (\min_{\gamma} (P_{\beta\gamma}), \min_{\gamma} (I_{\beta\gamma}), \max_{\gamma} (N_{\beta\gamma})) \right\}
$$
\n(4.12)

Step-6 Calculate the Euclidean distance of aggregated spherical fuzzy information from the positive and negative ideal solutions as follows

$$
ED_{\beta\gamma}^{+} = \sqrt{\frac{1}{n} \left[\frac{\sum_{\beta=1}^{q} \sum_{\gamma=1}^{j} (P_{\beta\gamma} - (\max_{\gamma} (P_{\beta\gamma})))^{2}}{\sum_{\beta=1}^{q} \sum_{\gamma=1}^{j} (I_{\beta\gamma} - (\min_{\gamma} (I_{\beta\gamma})))^{2}} \right]}
$$
\n
$$
\sum_{\beta=1}^{q} \sum_{\gamma=1}^{j} (N_{\beta\gamma} - (\min_{\gamma} (\gamma_{\beta\gamma})))^{2}}
$$
\n(4.15)

and

$$
ED_{\beta\gamma}^{-} = \sqrt{\frac{1}{n} \left[\frac{\sum_{\beta=1}^{q} \sum_{\gamma=1}^{j} (P_{\beta\gamma} - (\ln \left(\frac{\beta\gamma}{\beta\gamma})\right))^{2} + \sqrt{\sum_{\beta=1}^{q} \sum_{\gamma=1}^{j} (\ln \left(\frac{\beta\gamma}{\beta\gamma}\right))^{2} + \sqrt{\sum_{\beta=1}^{q} \sum_{\gamma=1}^{j} (\ln \left(\frac{\beta\gamma}{\beta\gamma}\right))^{2} - \sqrt{\ln \left(\frac{\beta\gamma}{\beta\gamma}\right))^{2}}}\right] \tag{4.14}
$$

Step-7 Closeness lation to ideal solutions are calculated as follows

$$
\mu_{\mu} = E D_{\beta\gamma}^{-} + E D_{\beta\gamma}^{-} \tag{4.15}
$$

To ranked the set of paths (alternatives) by preferce according to the descending order of μ_{β} . Means highest μ _β will be our finest path (alternative).

Flow chart of the proposed technique is given in Fig. [2:](#page-7-0)

5 Application

To study the prevention and control of COVID-19, we have developed a novel hybrid methodology for selecting the best alternatives using a critical path strategy that will help to choose the best path to overcome this deadly disease.

Case Study: To demonstrate the applicability and validity of the proposed methods, we extant a real case study about an emergency caused by an outbreak of novel Coronavirus disease (COVID-19) pandemic that occurred in C ina.

Since 19 December 2020, in Wuhan, Ch_n there have been several unidentified cases of pneumonia with cough, dyspnea, exhaustion and f or as the major symptoms reported in a short time. The chinese health officials and CDC immediately identified the pathogen of these cases as a new form of coronavirus which was called COVID-19 by the Worl[d](#page-16-14) Health Organization (WHO) on 10 Janvary-20 (World 2020). The Cninese government's information department held a press conference on pneumonia prevention and control of new coronavirus infections on January 22, 2020. The same day, $\sqrt{\sin 2gy}$ for the prevention and control of pneumonitis of n_{ew} coronavirus infection was announced by the Peo_p a's Republic of China, along with COVID-19 epidemic research, sample collection and testing, monitoring and man a_g agent of close contacts, and public propaganda, education and risk communication (Shen et al. 2020). The $p_1 \times p_2 \times 1$ and $(p_1^2, p_2^2, \ldots, p_n^2)$
 $\therefore p_2 \times p_3 \times 1$ also as **Study** To demonstrate the reputation of the distribution of the distribution of the top of the proposition and reduced to the specific proposition

As of May 4, 2020, more than 3 442 234 confirmed cases and 239 740 confirmed deaths are reported in 215 Countries, areas or territories. The infected cases graph are as follows in Fig. 3:

In such emergency situation, it is essential to provide an efficient way in emergency response for avoiding additional losses and to save the lives of the people. Preventive and mitigation measures are key in both health care and community settings. Due to such an emergency decision, the health experts have to make an immediate response, urgently rescue to control the situation efficiently and stop it from more deaths.

The panel of three experts ratings on the set of criteria are collected and illustrated for each activity shown in Tables [1,](#page-9-0) 2.

Step-1 Decision makers activities information computed in spherical fuzzy sets using Table 2:

St[e](#page-16-13)p-2(a) Utilizing (Yue [2011](#page-16-13)) methodology to find the average *D*∗, left negative *L D*− and right negative *R D*− ideal solutions are given as follows

Fig. 3 Infected cases

Step-2(b) We find the SM_k , SM_k^{l-} and SM_k^{R-} by using formulas of Step-2(b).

- **Step-2(c)** The final closedness coefficient values are obtained using Eq[.4.8](#page-5-0) and
- **Step-2(d)** Weights using Eq[.4.9](#page-5-1) are follows as $\n b_1$ 0.3562 b_2 0.3076 b_3 0.3362
- **Step-3** Calculate the aggregated matrix by using spherical fuzzy weighted averaging operator defined in Eq. [4.10](#page-5-2) in Table $3(a)$ $3(a)$, (b).

There is a panel of experts to determined the critical path (given in (Fig. [4\)](#page-10-2)) for prevent and control of COVID-19 with respect to the following criteria's:

Table 2 Linguistic variables and their corresponding SFNs

Step-5 Calculate the Positive ideal $(\rho_{\beta\gamma}^+)$ and negative ideal $(\rho_{\beta\gamma}^-)$ solution by using Eq.4.11 and Eq[.4.12.](#page-6-2)

$$
\rho_{\beta\gamma}^{+} = \left\{ \begin{array}{l} (0.430, 0.00, 0.043), (0.536, 0.00, 0.004), \\ (0.458, 0.00, 0.006), (0.526, 0.00, 0.008), \\ (0.547, 0.00, 0.003) \end{array} \right\}
$$

and

$$
\rho_{\beta\gamma}^{-} = \begin{cases}\n(0.140, 0.00, 0.414), (0.367, 0.00, 0.128), \\
(0.309, 0.00, 0.162), (0.333, 0.00, 0.186), \\
(0.362, 0.00, 0.030)\n\end{cases}
$$

- **Step-6** Calculate the Euclidean distance of aggregated spherical fuzzy information from the positive and negative ideal solutions by using Eqs. [4.13](#page-6-3) and [4.14](#page-6-4) as follows in Table $5(a)$ $5(a)$:
- **Step-7** Calculate the closeness relation value by using Eq. 4.15. and Final ranking are as follows in $\frac{4.15}{9}$ (b):

6 Comparison analysis

In the following, we will demonstrate the effectiveness and advantages of proposed cerators by comparing with the existing methods. The **finally** ranks alternatives (paths) are similar. In view of this the a_1 roach proposed is valid. Table [6](#page-13-1) displays the final results of the proposed approach and TOP-SIS process.

In addition, conparisons of the current approach with the preceding s studies to clearly clarify the implications of the proposed a p_proach are displayed in Table 7.

Additionally, the comparisons between two forms of fuzzy sets be shown in Table 8. As can be shown, under IFSs and PFSs nvironments, the essential path of the project network remains the same; however, other ranks (project paths) have been modified. With all of this in view, the SF sets may under-

Table 3 Agg

stand uncertainty better than the existing fuzzy set structure. The critical path of the network is identified correctly by using the proposed methodology. As a result, project scheduling and planning may be closely related to reality. In fact, in an uncertain environment, the critical path of the projects and the degree of criticality of each path are specified.

6.1 Method flexibility with various input and outputs

The proposed methodology are flexible, and can be efficiently used for various input and output circumstances. Because of the different score functions and its generalization, the

Table 4 Aggregated information in paths

ranking of the propose tec nique seems to differ little. This model is more $e^{r\phi}$ cie. \tan most because, in decisionmaking methods, spherical \mathbf{h} zy set increases grade space and can variate a cording to the emergency situations.

comparison with other frameworks

Fuzzy set, intuitionistic FS, picture FS have some space limitation on their grades. Spherical FS fills this gap in the literature and offers significant space than FS, intuitionistic FS, picture FS. The suggested framework enhances existing approaches and the decision-maker can choose the grades freely by using the condition $0 \le P_b^2 + I_b^2 + N_b^2 \le 1$.

6.3 Limitations

The limitation of this analysis is that the developed model determines the best alternative in a single setting based on the input of considered experts.

7 Conclusion

The novel 2019 Coronavirus, SARS-CoV-2 (COVID-19), originated in the city of Wuhan in the People's Republic of China's Hubei province towards the end of 2019 and has spread very quickly in a very short time to the world. This article aimed to analyze the pandemic trajectory using mathematical modeling based on the information used by fuzzy decision making methodology to select the best alternative using critical path strategy.

Spherical fuzzy set plays a vital role in solving emergency decision making in the emergency situation of COVID-19,

Table 5 (a): Aggregated distance. (b): Closeness relation value and final ranks of each alternative

Bold value indicates the best alternative in critical path strategy

Bold value indicates the best alternative in critical path strategy

Table 8 Comparison with PyF sets

Bold value indicates the best alternative in critical path strategy

as they can optimal describe a prefer nce when there is vague or uncertain information. In this study, a new integrated TOPSIS-COPRAS approach is established to handle emergency MCGDM problems with unknown weight information. The presented approach simultaneously considers a DMs' limiting rationality and interdependence among criteria. The objective weight vectors are obtained by using the distance measure and were combined with subjective weights in the spherical fuzzy MCGDM model. Moreover, the operation of the proposed method is thoroughly explained with the assistance of a numerical example on the basis of the ⁷OP IS-CO *RAS* method. We testified the effectiveness and r_{on} of the proposed MCGDM approach, its output is compared with other MCGDM problems to make a comparison. The proposed MCGDM approach can also be used to other complicated problems like risk evaluation, emerging technology, uncertain decision-making, project installation, site selection etc.

The approach proposed in this paper will be extended in future research to other ambiguous fields, such as linguistic term sets, probabilistic linguistic term sets, hesitant fuzzy sets etc. The suggested approach can also be extended to other fields, such as medical diagnosis of nutrition, sustain-

able choice of suppliers, pattern recognition and so on. We will also try to extend this work for interval valued spherical fuzzy environments.

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Compliance with Ethical Standards

Conflict of interest The authors declare that they have no conflict of interest.

Ethical approval: This article does not contain any studies with human participants or animals performed by any of the authors.

References

Amiri M, Golozari F (2011) Application of fuzzy multi-attribute decision making in determining the critical path by using time, cost, risk, and quality criteria. Int J Adv Manuf Technol 54(1–4):393– 401

- Ashraf S, Abdullah S, Mahmood T (2018) GRA method based on spherical linguistic fuzzy Choquet integral environment and its application in multi-attribute decision-making problems. Math Sci 12:263–275
- Ashraf S, Abdullah S (2019) Spherical aggregation operators and their application in multi-attribute group decision-making. Int J Intell Syst 34(3):493–523
- Ashraf S, Abdullah S, Mahmood T, Ghani F, Mahmood T (2019) Spherical fuzzy sets and their applications in multi-attribute decision making problems. J Intell Fuzzy Syst 36:2829–2844
- Ashraf S, Abdullah S, Aslam M, Qiyas M, Kutbi MA (2019) Spherical fuzzy sets and its representation of spherical fuzzy t-norms and tconorms. J Intell Fuzzy Syst. https://doi.org/10.3233/JIFS-181941
- Ashraf S, Abdullah S, Mahmood T (2019) Spherical fuzzy Dombi aggregation operators and their application in group decision making problems. J Ambient Intell Humaniz Comput. https://doi.org/ 10.1007/s12652-019-01333-y
- Ashraf S, Abdullah S, Abdullah L (2019) Child development influence environmental factors determined using spherical fuzzy distance measures. Mathematics 7(8):661
- Ashraf S, Mahmood T, Abdullah S, Khan Q (2019) Different approaches to multi-criteria group decision making problems for picture fuzzy environment. Bull Braz Math Soc New Ser 50(2):373–397
- Ashraf S, Abdullah S, Mahmood T, Aslam M (2019) Cleaner production evaluation in gold mines using novel distance measure method with cubic picture fuzzy numbers. Int J Fuzzy Syst 21(8):2448–2461
- Ashraf S, Abdullah S, Aslam M (2020) Symmetric sum based aggregation operators for spherical fuzzy information: application in multi-attribute group decision making problem. J Intell Fuzzy Syst 38(4):5241–5255
- Ashraf S, Abdullah S, Zeng S, Jin H, Ghani F (2020) Fuzzy decision support modeling for hydrogen power plant selection based as single valued neutrosophic sine trigonometric aggregation. pera Symmetry 12(2):298
- Attanassov K (1986) Intuitionistic fuzzy sets. Fuzzy S $\frac{1}{5}$ System 20:87–96
- Atanassov K (2018) Intuitionistic fuzzy interpretations of Barcan formulas. Inf Sci 460:469–475
- Atanassov K (2018) On the most extended modal operator of first type over interval-valued intuitionistic fuzzy sets. Mathematics 6(7):123
- Atanassov K (2015) Intuitionistic fuzzy logical cools for evaluation of data mining processes. Knowl-Based Syst 80:122-130
- Barukab O, Abdullah S, Ashraf N, Khan SA (2019) A new approach to fuzzy $T O_P$ S measure based on entropy measure under spherical fuzzy information. Entropy 21(12):1231
- Boran FE, Genç S, Kurt M, Akay D (2009) A multi-criteria intuitionistic fuzzy group α vision vaking for supplier selection with TOPSIS method. Expert Syst A_p $\angle 36(8):11363-11368$
- Cao H, Zhang R, Yang J (2019) Some spherical linguistic Muirhead mean operators with their application to multi-attribute decision g. J Intelligency Syst. https://doi.org/10.3233/JIFS-190566
- Crowell I. Peacock SJ, Mitton C (2015) 'Real-world'health care priv setting using explicit decision criteria: a systematic review of the literature. BMC Health Serv Res 15(1):164
- Chen CT (2000) Extensions of the TOPSIS for group decision-making under fuzzy environment. Fuzzy Sets Syst 114(1):1–9
- Churchman CW, Ackoff RL, Arnoff EL (1957) Introduction to operations research
- Cuong BC, Kreinovich V (2013) Picture fuzzy sets-a new concept for computational intelligence problems. In: Proceedings of 3rd world congress on information and communication technologies (WICT), pp 1–6
- Dorfeshan Y, Mousavi SM (2019) A new group TOPSIS-COPRAS methodology with Pythagorean fuzzy sets considering weights of experts for project critical path problem. J Intell Fuzzy Syst. [https://](https://doi.org/10.3233/JIFS-172252) doi.org/10.3233/JIFS-172252
- Gündoğdu FK, Kahraman C Hospital performance assessment using interval-valued spherical fuzzy analytic hierarchy process. In: Decision making with spherical fuzzy sets. Springer, Cham, pp 349–373 (2020)
- Gündoğdu FK, Kahraman C Optimal site selection of electric vehicle charging station by using spherical fuzzy TOPSIS method. In: Decision making with spherical fuzzy sets. Springer, Cham, pp 201–216 (2020)
- Gündoğdu FK, Kahraman C (2020) A novel spherical fuzzy QFD method and its application to the linear delta robot chnology development. Eng Appl Artif Intell 87:103248
- Gündoğdu FK, Kahraman C (2019) A novel 1. v TOP IS method using emerging interval-valued spherical fuz. sets. Eng Appl Artif Intell 85:307–323
- Gündoğdu FK, Kahraman C (2020) A vel spherical fuzzy analytic hierarchy process and its renewable to the plication. Soft Comput 24(6):4607–4621
- Hwang CL, Yoon K (1981⁾ Methods for multiple attribute decision making. In: Multip¹ att. vte decision making. Springer, Berlin, pp 58–191
- Jin Y, Ashraf S, Abdullah S (2019) Spherical fuzzy logarithmic aggregation operators based on entropy and their application in decision support systems. Entropy 21:628. https://doi.org/10. 3390/e21070628
- Jin H, Ashraft S, Abdullah S, Qiyas M, Bano M, Zeng S (2019) Linguistic spherical fuzzy aggregation operators and their applications in multi-attribute decision making problems. Mathematics $7(5):413$ man C, Gündoğdu FK (2020) Decision making with spherical tzy sets: theory and applications. Springer, Berlin System than the main control of the same the proposed into the same the same of the same
	- Khan J, IJ, Kumam P, Ashraf S, Kumam W (2019) Generalized picture fuzzy soft sets and their application in decision support systems. Symmetry 11(3):415
	- Khan S, Abdullah S, Ashraf S (2019) Picture fuzzy aggregation information based on Einstein operations and their application in decision making. Math Sci 13:213–229
	- Khan MJ, Kumam P, Deebani W, Kumam W, Shah Z (2020) Distance and similarity measures for spherical fuzzy sets and their applications in selecting mega projects. Mathematics 8(4):519
	- Khan MJ, Kumam P, Liu P, Kumam W (2020) An adjustable weighted soft discernibility matrix based on generalized picture fuzzy soft set and its applications in decision making. J Intell Fuzzy Syst 38(2):2103–2118
	- Kumar PM, Gandhi U, Varatharajan R, Manogaran G, Jidhesh R, Vadivel T (2017) Intelligent face recognition and navigation system using neural learning for smart security in Internet of Things. Cluster Comput 22:7733–7744
	- Karaca Z, Onargan T (2007) The application of critical path method (CPM) in workflow schema of marble processing plants. Mater Manuf Process 22(1):37–44
	- Khan S, Abdullah S, Abdullah L, Ashraf S (2019) Logarithmic aggregation operators of picture fuzzy numbers for multi-attribute decision making problems. Mathematics 7(7):608
	- Kildienė S, Kaklauskas A, Zavadskas EK (2011) COPRAS based comparative analysis of the European country management capabilities within the construction sector in the time of crisis. J Bus Econ Manag 12(2):417–434
	- Mehlawat MK, Gupta P (2016) A new fuzzy group multi-criteria decision making method with an application to the critical path selection. Int J Adv Manuf Technol 83(5–8):1281–1296
	- Mendel JM, Eyoh I, John R (2019) Comparing performance potentials of classical and intuitionistic fuzzy systems in terms of sculpting the state space. IEEE Trans Fuzzy Syst. [https://doi.org/10.1109/](https://doi.org/10.1109/TFUZZ.2019.2933786) [TFUZZ.2019.2933786](https://doi.org/10.1109/TFUZZ.2019.2933786)
	- Mendel JM, Chimatapu R, Hagras H (2019) Comparing the performance potentials of singleton and non-singleton type-1 and interval

type-2 fuzzy systems in terms of sculpting the state space. IEEE Trans Fuzzy Syst 28(4):783–794

- Mendel JM (2019) Adaptive variable-structure basis function expansions: candidates for machine learning. Inf Sci 496:124–149
- Nag K, Helal M (2016) A fuzzy TOPSIS approach in multi-criteria decision making for supplier selection in a pharmaceutical distributor. In: 2016 IEEE international conference on industrial engineering and engineering management (IEEM). IEEE, pp 1126–1130
- Rafiq M, Ashraf S, Abdullah S, Mahmood T, Muhammad S (2019) The cosine similarity measures of spherical fuzzy sets and their applications in decision making. J Intell Fuzzy Syst 36:6059–6073
- Shen M, Peng Z, Xiao Y (2020) Modeling the epidemic trend of the 2019 novel coronavirus outbreak in China. bioRxiv. https://doi. org/10.1101/2020.01.23.916726
- Sotirov S, Sotirova E, Atanassova V, Atanassov K, Castillo O, Melin P, Petkov T, Surchev S (2018) A hybrid approach for modular neural network design using intercriteria analysis and intuitionistic fuzzy logic. Complexity. https://doi.org/10.1155/2018/3927951
- Sotirov S, Sotirova E, Melin P, Castilo O, Atanassov K (2016) Modular neural network preprocessing procedure with intuitionistic fuzzy intercriteria analysis method. In: Flexible query answering systems 2015. Springer, Cham, pp 175–186
- Castillo O, Melin P, Tsvetkov R, Atanassov KT (2015) Short remark on fuzzy sets, interval type-2 fuzzy sets, general type-2 fuzzy sets and intuitionistic fuzzy sets. In: Intelligent systems' 2014. Springer, Cham, pp 183–190
- Wang YM, Elhag TM (2006) Fuzzy TOPSIS method based on alpha level sets with an application to bridge risk assessment. Expert Syst Appl 31(2):309–319
- Wang L, Peng JJ, Wang JQ (2018) A multi-criteria decision-making framework for risk ranking of energy performance contracting project under picture fuzzy environment. J Clean Prod 191:105 118 Lis 2016 Belle interactions and spin and s
- Wei G (2017) Picture fuzzy aggregation operators and their application to multiple attribute decision making. J Intell Fuzzy Syst 33(2):713–724
- World Health Organization (WHO) Coronavirus 2020
- Yager RR (2013) Pythagorean fuzzy subsets. In: 2013 joint IFSA world congress and NAFIPS annual meeting (IFSA/NAFIPS). IEEE, pp 57–61
	- Yue Z (2011) A method for group decision-making based on determining weights of decision makers using TOPSIS. A_{ν} , Math Model 35(4):1926–1936
	- Zadeh L (1965) Fuzzy sets. Inf Control 8:338-353
	- Zeng S, Hussain A, Mahmood T, Irfan Ali M, Ashraf S, Munir M (2019) Covering-based spherical fuzzy rough set model hybrid with TOP-SIS for multi-attribute decision-making. Symmetry 11(4):547
	- Zeng S, Asharf S, Arif M, Abdullah S (209) Application of exponential jensen picture fuzzy divergence measure in multi-criteria group decision making. Mathematics 7:191
	- Zammori FA, Braglia M, \overline{Y} osolini M (2009) A fuzzy multi-criteria approach for critica^l path definition. Int J Proj Manag 27(3):278– 291
	- Zavadskas EK, Kaklauskas A (1996) Multiple criteria evaluation of buildings. Village Lithuania

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