Application of Generalized Fuzzy TOPSIS in Decision Making for Neutrosophic Soft set to Predict the Champion of FIFA 2018: A Mathematical Analysis

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Abstract

Predicting the outcomes of soccer matches is curious to numerous; from fans to supporters. Prediction about the outcomes of soccer matches is also very exciting and enticing as a research problem, especially due to its complications, exertion, unexpected inferences etc. Consequently, a soccer match is relying upon various factors, actors and unpredictable situations. Therefore, it is very agonizing and uphill task to predict the meticulous and close to truth-based results of soccer matches. Such a research demands a multi-criteria decision-making approach, i.e. TOPSIS, to foresee accurate ranking and applied to the fallouts of FIFA 2018 world cup soccer matches explicitly. The match statistics have been used up to quarter finals, to make better estimates for the impending games. Outcomes proved prediction of approximately right ranking and outcomes of matches are substantially higher than those of reported through other means.

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1. Introduction

Soccer is possibly the World's pre-prominent diversion, so it isn't shocking that there has been a lot of research on soccer expectations. Truly, among all games, soccer forecast is a standout amongst the most comprehensively and strongly explored zone. These examinations commonly treat with scientific/factual portrayals or methodologies however there are a few explore dependent on Artificial Intelligence (AI) strategies [17].

Voluminous researchers proposed their models for the prediction of soccer matches results. Their mythologies reveal that their proposed techniques can be used for the forecast of soccer matches. The number of models and mythologies are suggested by the researchers, like, Poisson Regression Models (PRM), Strategic Regression (SR) which demonstrates the intra-match winning probability and many more are used to study the results of soccer matches [13], [1-4]. A large portion of these operations give certain expectations too, however, they are progressively mindful on the measurable investigation of the results of soccer matches. Crowder [1] implement his model to forecast, English Soccer Association League (EFAL) by using Poisson Regression Models (PRM) [2].

Statistical study in the prediction of soccer is also used in many investigations. Such a study, requires genuine information, for the implementation of the proposed technique. Statistical procedures are indistinguishable to many AI approaches. They utilize slight learning/data and are profoundly founded on unadulterated arithmetical models, for example, the probit model and Poisson models [6, 7, 11, 14, 15]. Some other works utilized models or strategies that are additional dependent on the information or knowledge of soccer matches [1, 6, 9, 11, 19]. Machine learning or AI-based techniques are normally used to forecast the soccer results, which include, Bayesian Learning (BL), Decision Tree (DT), Naive Bayesian Learning (NBL), Expert Bayesian Network (EBN) and K-nearest neighbor [3, 8, 12, 17, 18].

Related researches have offered some clashing decisions about the dissimilarities in the execution, among successful and failed teams throughout official matches. Consequently, the point of this research is to predict the outcomes of forthcoming soccer matches using MCDM technique and prediction related research based on current stats has been done.

In daily life issues for a suitable explanation of an entity in an uncertain and vague environment, we need to grip the indeterminate and incomplete information. But fuzzy sets (FS's) and intuitionistic fuzzy sets (IFS's) don't knob the indeterminant and erratic information. The notion of Neutrosophic set (NS) was defined by [21] which is a mathematical implementation for dealing with problems connecting imprecise and erratic information. The concept of soft set (SS) & NS was together by [16] presenting a new concept called Neutrosophic soft set (NSS) and gave an application of NSS in MCDM or MADM problems.

In this paper, the Generalized Fuzzy TOPSIS technique of MCDM is suggested to forecast the soccer matches the outcome of the last FIFA world cup 2018. To this end, some significant measures which theoretically affect the match outcomes are required. Consequently, a wide-ranging database of match statistics of the world cup is used up to quarterfinal matches. Then by implementing the proposed technique results are predicted. Saqlain *et. al.* [20] predicted the CWC 2019 by using the TOPSIS technique of MCDM.

2. Material and Method

The match related to arithmetical data, which is studied in this research is openly accessible from the FIFA website *https://www.fifa.com/* (FIFA, 2018). The stats of group stage match, of the 2018 FIFA World Cup is used to implement the proposed MCDM technique, the attributes of each team, which are used: shots, shots on target, fouls, offsides, yellow cards, red cards, corners, with possession of the ball and percentage of ball possession in each match played.

2.1 FIFA

International Federation of Association Football (FIFA) is an organization that describes itself as an international governing body of association football. FIFA is responsible for the organization of football's major international tournaments.

2.2 Sport Expert

The persons who have perfect knowledge about the soccer game. Those who know which attributes play an important role during the game like goals, corners, offsides, red cards, yellow cards, etc. are given the name sports expert. On behalf of their knowledge about the game, these persons are considered for the selection of attributes as taken in Table 1.

2.3 Opta

Opta Sports, formerly Opta Sports data, is an international sports analytics company based in the United Kingdom. Opta provides data for 30 sports in 70 countries, with clients ranging from leagues to broadcasters and betting websites. Opta debuted its current real-time data collection process for soccer matches in 2006, leading to an expansion in new data offerings across different sports.

2.4 TOPSIS and Generalized Fuzzy TOPSIS

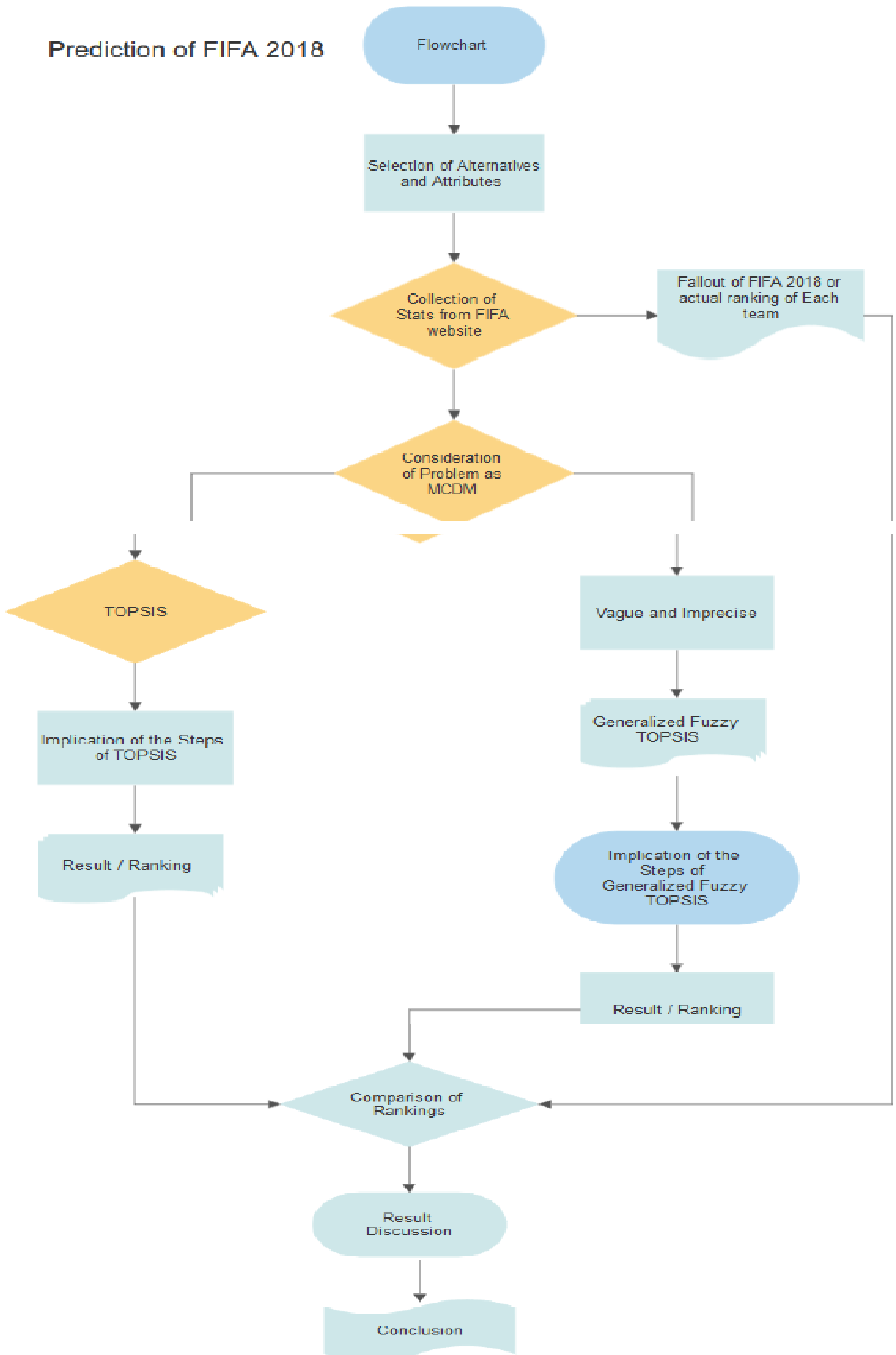
2.4.1 TOPSIS

The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) is a multi-criteria decision analysis method, which was originally developed by [23] in 1981.

2.4.2 Generalized Fuzzy TOPSIS

Based on the two operations Up and Lo, the FMCGDM method being the generalized TOPSIS in a fuzzy environment is presented in [22].

2.5 Algorithm



3. Calculations

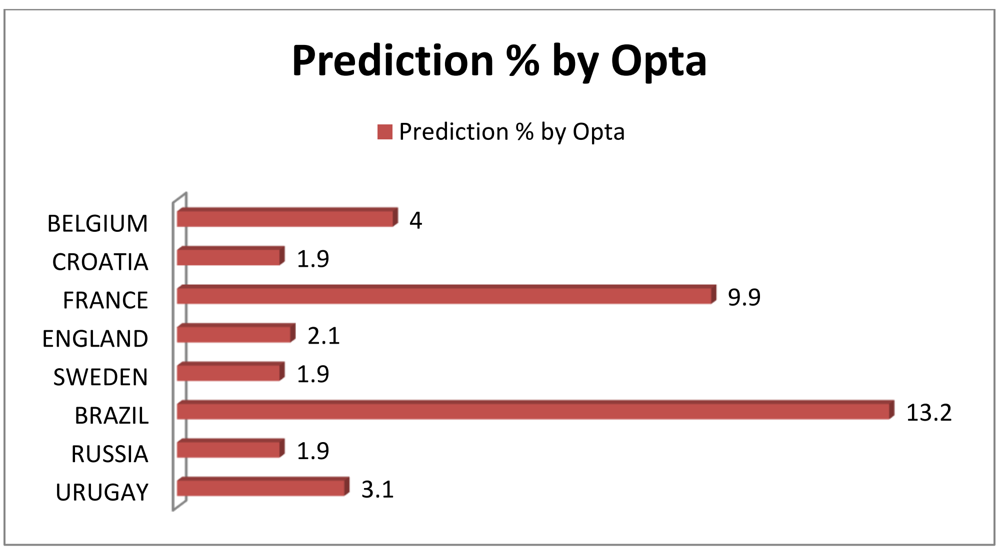
After setting prediction parameters and collecting required data than with proposed technique match results of the last world cup would be predictable. As eight top teams i.e. (Knockout Period) comprised of URUGUAY, RUSSIA, BRAZIL, SWEDEN, ENGLAND, FRANCE, CROATIA, BELGIUM have a chance to win the world cup. This research is done by considering the top eight teams from the Knockout period in future this research can be extended from eight to more teams. Initially, eight teams were considered for the calculations, in the future, these calculations can be applied to the statistics of the whole teams participating in the FIFA.

A prediction representative of the soccer, Opta predicted the percentage of winning the FIFA 2018 before the world cup as below.

Team	URUGUAY	RUSSIA	BRAZIL	SWEDEN	ENGLAND	FRANCE	CROATIA	BELGIUM
Prediction % by Opta	3.1	1.9	13.2	1.9	2.1	9.9	1.9	4

Table: 1 prediction percentage by Opta for Knockout teams

In the Opta model, each team has an attacking and defensive strength calculated based on past performances. Given these attacking and defensive strengths and several other World Cup-specific variables for each game we can assign a likelihood to each potential result (either team to win or a draw).



Graph: 1 Percentage of winning the FIFA 2018 given by Opta

3.1 Prediction by TOPSIS Technique

The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) is a multi-criteria decision analysis method. To apply the TOPSIS technique we need following data or information

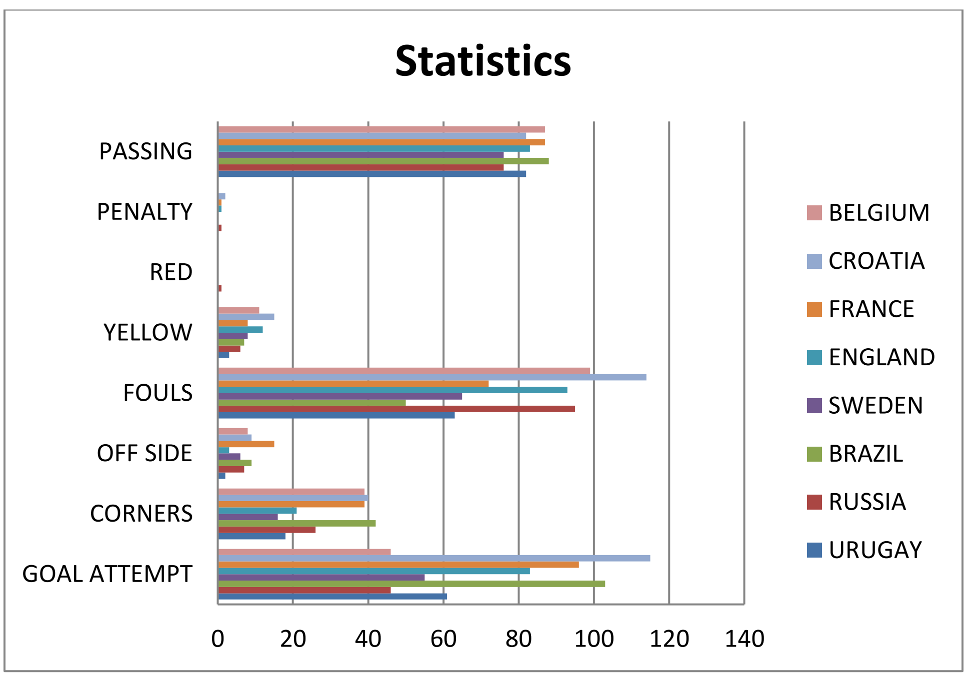
- Alternatives

- Attributes
- Attribute Values
- Weights

The match related to arithmetical data, which studied in this research is openly accessible from the FIFA website *https://www.fifa.com/* (FIFA, 2018). To implement the proposed MCDM technique, the subsequent actions (attributes) of the teams are systematized. Table: 2 shows the team as alternatives and statistics headings as attributes.

TEAMS	GOAL ATTEMPTS	CORNERS	OFFSIDE	FOULS	YELLOW	RED	PENALTY	PASSING
URUGUAY	61	18	2	63	3	0	0	82
RUSSIA	46	26	7	95	6	1	1	76
BRAZIL	103	42	9	50	7	0	0	88
SWEDEN	55	16	6	65	8	0	0	76
ENGLAND	83	21	3	93	12	0	1	83
FRANCE	96	39	15	72	8	0	1	87
CROATIA	115	40	9	114	15	0	2	82
BELGIUM	46	39	8	99	11	0	0	87

Table: 2 Attribute, alternatives and FIFA 2018 statistics up to quarter final which is considered for the calculations

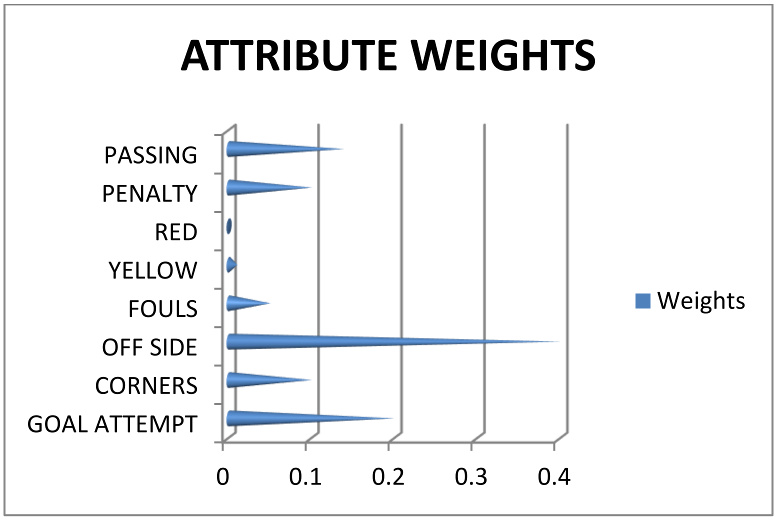


Graph: 2 Attribute, alternatives and FIFA 2018 statistics up to quarter-final which is considered for the calculations

ATTRIBUTES	GOAL ATTEMPT	CORNERS	OFFSIDE	FOULS	YELLOW	RED	PENALTY	PASSING
WEIGHTS	0.2	0.1	0.4	0.05	0.01	0.001	0.1	0.139

Table: 3 weights which are assigned by the sports experts to the attributes

In daily life issues for a suitable explanation of an entity in the uncertain and vague environment, we need to grip the indeterminate and incomplete information, especially when they involve a large set of attributes that require decision-makers to develop rankings.



Graph: 3 weights which are assigned by the sport experts to the attributes

3.2 TOPSIS Technique:

Step 1: Construct the Normalized Decision Matrix by using:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}$$

Step 2: Construct the Weighted Normalized Decision Matrix: $V_{ij} = w_j \, r_{ij}$

Step 3: Determine Ideal and Negative-Ideal Solutions:

$A^+ = \{ V_1, \dots, V_n \}$

$A^- = \{ V_1, \dots, V_n \}$

Step 4: Calculate the Separation Measure:

- Ideal Separation:

$$S_i^+ = \sqrt{\sum_{j=1}^{n} (V_{ij} - V_j^+)^2} \qquad i = 1,2,3, \dots, m$$

- Negative Ideal Separation:

$$S_i^- = \sqrt{\sum_{j=1}^{n} (V_{ij} - V_j^-)^2} \qquad i = 1,2,3, \ldots, m$$

Step 5: Calculate the Relative Closeness to the Ideal Solution:

$$C_i^* = \frac{S_i^-}{(S_i^+ + S_i^-)}, \; 0 < C_i^* < 1, \qquad i = 1,2,3, \ldots, m .$$

$$C_i^* = 1, \; if \; A_i = A^+ \quad \text{and} \quad C_i^* = 0, \; if \; A_i = A^-$$

Step 6: Rank the preference order a set of alternatives can now be preference ranked according to C_i^*.

S_i^+	S_i^-	C_i^*	**Result – rank**	**Team**
0.032124	0.297466	0.902535	**8**	URUGUAY
0.091397	0.204687	0.691313	**6**	RUSSIA
0.165902	0.133734	0.446323	**3**	BRAZIL
0.066375	0.222928	0.770569	**5**	SWEDEN
0.060273	0.267291	0.815996	**7**	ENGLAND
0.274337	0.035194	0.1137	**1**	FRANCE
0.176975	0.12929	0.422151	**2**	CROATIA
0.121585	0.183462	0.601422	**4**	BELGIUM

Table: 4 TOPSIS technique calculation results

3.3 Generalized Fuzzy TOPSIS:

Definition 1: A Fuzzy Neutrosophic FN set $\mathcal{A}$ over the universe of discourse $\mathcal{X}$ is defined as $\mathcal{A} = < x, T_{\mathcal{A}}(x), I_{\mathcal{A}}(x), F_{\mathcal{A}}(x) >, \; x \in \mathcal{X} \; where \; T, F, I: \mathcal{X} \to [0,1]$ & $0 \leq T_{\mathcal{A}}(x) + I_{\mathcal{A}}(x) + F_{\mathcal{A}}(x) \leq 3$.

Definition 2: Let $\mathcal{X}$ be the initial universal set and Ē be a set of parameters. Consider a non-empty set $\mathcal{A}$, $\mathcal{A} \subset$ Ē. Let Ƥ ($\mathcal{X}$) denote the set of all FN sets of $\mathcal{X}$.

Fuzzy Sets (FS's) don't knob the indeterminant and erratic information while dealing with uncertainty and vague environment. Neutrosophic Set (NS's) is the mathematical implementation for dealing with problems connecting imprecise and erratic information. So, in this section, Neutrosophic soft set (NSS) is considered for the calculations.

Let $U = \{A_1, A_2, A_3, A_4, A_5, A_6, A_7, A_8\}$ be the set of alternatives, and consider $E = \{C_1, C_2, C_3, C_4, C_5, C_6, C_7, C_8\}$ be a set of attributes as shown in table: 5 and table: 6 respectively.

TEAMS AS ALTERNATIVES	ACTUAL RANKS
$\boldsymbol{A_1}$ =URUGAY	6
$\boldsymbol{A_2}$ =RUSSIA	7
$\boldsymbol{A_3}$ =BRAZIL	5
$\boldsymbol{A_4}$ =SWEDEN	8
$\boldsymbol{A_5}$ =ENGLAND	4
$\boldsymbol{A_6}$ =FRANCE	1
$\boldsymbol{A_7}$ =CROATIA	2
$\boldsymbol{A_1}$ =BELGIUM	3

Table: 5 sets of alternatives as A_i

C_1 =Goal Attempt
C_2 =Corner
C_3 =Off side play
C_4 =Fouls
C_5 =Yellow Cards
C_6 =Red Cards
C_7 =Peualty Corners
C_8 =Passing %

Table: 6 Set of attributes as C_i

Step 1: Assigned the suitable rating in terms of a linguistic variable by the experts for each criterion.

Step 2: Assigning suitable rating in terms of Neutrosophic Soft Sets (NSS's) to each linguistic variable by the experts for each criterion.

	$\boldsymbol{A_1}$	$\boldsymbol{A_2}$	$\boldsymbol{A_3}$	$\boldsymbol{A_4}$
$\boldsymbol{C_1}$	(0.41, 0.7, 0.59)	(0.31, 0.5, 0.69)	(0.67, 0.9, 0.33)	(0.38, 0.6, 0.62)
$\boldsymbol{C_2}$	(0.47, 0.3, 0.53)	(0.65, 0.63, 0.35)	(1.0, 0.93, 0.1)	(0.49, 0.61, 0.51)
$\boldsymbol{C_3}$	(0.15, 0.3, 0.85)	(0.45, 0.6, 0.55)	(0.6, 0.8, 0.4)	(0.41, 0.49, 0.59)
$\boldsymbol{C_4}$	(0.43, 0.9, 0.57)	(0.63, 0.7, 0.37)	(0.35, 0.3, 0.65)	(0.44, 0.2, 0.56)
$\boldsymbol{C_5}$	(0.21, 0.7, 0.79)	(0.43, 0.8, 0.57)	(0.49, 0.6, 0.51)	(0.54, 0.4, 0.46)
$\boldsymbol{C_6}$	(0.0, 0.1, 0.0)	(0.0, 0.11, 0.2)	(0.0, 0.20, 0.0)	(0.0, 0.19, 0.1)
$\boldsymbol{C_7}$	(0.0, 0.7, 0.13)	(0.01, 0.1, 0.09)	(0.03, 0.2, 0.0)	(0.01, 0.3, 0.03)
$\boldsymbol{C_8}$	(0.83, 0.7, 0.17)	(0.77, 0.6, 0.3)	(0.87, 0.3, 0.13)	(0.77, 0.89, 0.23)

Table: 7 (a) Suitable rating to each criterion in term of Neutrosophic by the decision makers

	A_5	A_6	A_7	A_8
C_1	(0.55, 0.86, 0.45)	(0.64, 0.9, 0.36)	(0.87, 0.5, 0.22)	(0.31, 0.6, 0.69)
C_2	(0.52, 0.81, 0.48)	(0.98, 1.0, 0.02)	(1.0, 0.98, 0.4)	(1.0, 0.7, 0.3)
C_3	(0.21, 0.9, 0.79)	(1.0, 1.0, 0.3)	(0.61, 1.0, 0.39)	(0.53, 0.31, 0.47)
C_4	(0.63, 0.4, 0.37)	(0.48, 0.51, 0.52)	(0.81, 0.47, 0.19)	(0.69, 0.31, 0.31)
C_5	(0.89, 0.3, 0.21)	(0.54, 0.37, 0.9)	(1.0, 0.9, 0.7)	(0.71, 0.63, 0.39)
C_6	(0.0, 0.2, 0.2)	(0.0, 0.3, 0.1)	(0.0, 0.13, 0.13)	(0.0, 0.17, 0.01)
C_7	(0.0, 0.7, 0.03)	(0.0, 0.1, 0.03)	(0.0, 0.0, 0.0)	(0.0, 0.1, 0.3)
C_8	(0.81, 0.9, 0.19)	(0.89, 0.7, 0.11)	(0.81, 0.9, 0.19	(0.89, 0.7, 0.13)

Table: 7(b) Suitable rating to each criterion in term of Neutrosophic by the decision makers

Step 3: Now find

$A^- = (G^-{}_1, G^-{}_2 \dots \dots . G^-{}_5)$ and $A^+ = (G^+{}_1, G^+{}_2 \dots \dots . G^+{}_5)$

$G^+{}_1 = (0.78, 0.90, 0.69)$; $G^-{}_1 = (0.31, 0.50, 0.22)$

$G^+{}_2 = (1.00, 1.00, 0.53)$; $G^-{}_2 = (0.47, 0.30, 0.10)$

$G^+{}_3 = (1.00, 1.00, 0.85)$; $G^-{}_3 = (0.15, 0.30, 0.30)$

$G^+{}_4 = (0.80, 0.90,0.65)$; $G^-{}_4 = (0.35\ 0.20, 0.19)$

$G^+{}_5 = (1.00, 0.90, 0.90)$; $G^-{}_5 = (0.21, 0.30, 0.21)$

$G^+{}_6 = (0.00, 0.30, 0.20)$; $G^-{}_6 = (0.00, 0.10, 0.00)$

$G^+{}_7 = (0.01, 0.70, 0.30)$; $G^-{}_7 = (0.00, 0.00, 0.00)$

$G^+{}_8 = (0.89, 0.90, 0.23)$; $G^-{}_8 = (0.77, 0.30, 0.11)$

Step 4: By using following formula

$$d(A, B) = \sqrt{(1\backslash 3)[(a_1 + b_1)^2 + (a_2 + b_2)^2 + (a_3 + b_3)^2]}$$

	A_1		A_2		A_3		A_4	
	$d(G_{1j}, G^{+}{}_j)$	$d(G_{1j}, G^{-}{}_j$	$d(G_{2j}, G^{+}{}_j)$	$d(G_{2j}, G^{-}{}_j$	$d(G_{3j}, G^{+}{}_j)$	$d(G_{3j}, G^{-}{}_j$	$d(G_{4j}, G^{+}{}_j)$	$d(G_{4j}, G^{-}{}_j$
C_1	0.2496	0.2496	0.3563	0.2714	0.2173	0.3171	0.2915	0.2415
C_2	0.5069	0.2483	0.3119	0.2606	0.2743	0.4753	0.3709	0.2970
C_3	0.6357	0.4330	0.4291	0.3571	0.3663	0.4252	0.4746	0.3385
C_4	0.2242	0.4622	0.2242	0.3468	0.4365	0.2718	0.4601	0.2198
C_5	0.4748	0.4068	0.3846	0.3777	0.4091	0.2935	0.4673	0.2459
C_6	0.1633	0.000	0.1097	0.1156	0.1291	0.0577	0.0858	0.0777
C_7	0.0983	0.4111	0.3670	0.0779	0.3180	0.1236	0.2786	0.1742
C_8	0.1254	0.2361	0.1909	0.2050	0.3514	0.0589	0.0695	0.3476

	A_5		A_6		A_7		A_8	
	$d(G_{5j}, G^{+}{}_j)$	$d(G_{5j}, G^{-}{}_j$	$d(G_{6j}, G^{+}{}_j)$	$d(G_{6j}, G^{-}{}_j$	$d(G_{7j}, G^{+}{}_j)$	$d(G_{7j}, G^{-}{}_j$	$d(G_{8j}, G^{+}{}_j)$	$d(G_{8j}, G^{-}{}_j$
C_1	0.1988	0.2624	0.2070	0.3101	0.3563	0.2714	0.3219	0.2796
C_2	0.2994	0.3683	0.2947	0.5022	0.0756	0.5270	0.2478	0.4896
C_3	0.4610	0.5291	0.3175	0.6461	0.3482	0.5118	0.5296	0.3063
C_4	0.3468	0.2242	0.3044	0.2720	0.3635	0.3080	0.3992	0.2176
C_5	0.5317	0.3926	0.4052	0.4434	0.1155	0.6388	0.3729	0.3612
C_6	0.1291	0.1156	0.0577	0.1291	0.1061	0.0770	0.1329	0.0408
C_7	0.3958	0.0440	0.3799	0.0603	0.4397	0.000	0.3465	0.1826
C_8	0.0516	0.3502	0.1347	0.2411	0.516	0.3502	0.1291	0.2414

Table: 8 Calculation of ideal distance as of Step: 2 of TOPSIS technique of MCDM

Step 5: The average weight assigned against each criterion.

$$w_1 = (0.51, 0.69, 0.49)\ w_2 = (0.76, 0.75, 0.34)\ w_3 = (0.50, 0.68, 0.54)$$

$$w_4 = (0.56, 0.47, 0.44)\ w_5 = (0.60, 0.59, 0.57)\ w_6 = (0.00, 0.18, 0.09)$$

$w_7 = (0.01, 0.20, 0.09)$ $w_8 = (0.83, 0.71, 0.18)$

Step 6: Calculation of weight distance value by using formula:

$D^+{}_i = \sum_{i=1}^{m} W_j \times d^+{}_{ij}$ & $D^-{}_i = \sum_{i=1}^{m} W_j \times d^-{}_{ij}$

$D^+{}_1 = (1.3459, 1.5083, 1.0533)$ & $D^-{}_1 = (1.2355, 1.3600, 0.9553)$

$D^+{}_2 = (1.1517, 1.3325, 0.9075)$ & $D^-{}_2 = (1.1068, 1.1933, 0.8366)$

$D^+{}_3 = (1.2872, 1.3876, 0.9263)$ & $D^-{}_3 = (1.1140, 1.3357, 0.9071)$

$D^+{}_4 = (1.2664, 1.3616, 1.0393)$ & $D^-{}_4 = (0.8194, 0.9415, 0.6679)$

$D^+{}_5 = (1.1194, 1.2909, 0.9603)$ & $D^-{}_5 = (1.3305, 1.4323, 0.9393)$

$D^+{}_6 = (1.0175, 1.1439, 0.8016)$ & $D^-{}_6 = (1.4819, 1.6259, 1.1045)$

$D^+{}_7 = (1.1190, 1.2519, 0.7562)$ & $D^-{}_7 = (1.6413, 1.7147, 1.1581)$

$D^+{}_8 = (1.1752, 1.3606, 0.9826)$ & $D^-{}_8 = (1.2075, 1.2975, 0.8330)$

Thus

$UD^+ = (1.3459, 1.5083, 1.0533)$, $LD^+ = (1.0175,\ 1.1439,\ 0.7562)$

$UD^- = (1.6413,\ 1.7147,\ 1.1581)$, $LD^- = (0.8194,\ 0.9415,\ 0.6679)$

Step 7: Find by using distance formula

$$d(A, B) = \sqrt{(1\backslash 3)[(a_1 + b_1)^2 + (a_2 + b_2)^2 + (a_3 + b_3)^2]}$$

$d(D^+{}_1, UD^+) = 0$ $d(D^+{}_1, LD^+) = 0.3311$

$d(D^+{}_2, UD^+) = 0.1731$ $d(D^+{}_2, LD^+) = 0.1597$

$d(D^+{}_3, UD^+) = 0.1067$ $d(D^+{}_3, LD^+) = 0.2317$

$d(D^+{}_4, UD^+) = 0.0967$ $d(D^+{}_4, LD^+) = 0.2567$

$d(D^+{}_5, UD^+) = 0.189$ $d(D^+{}_5, LD^+) = 0.1567$

$d(D^+{}_6, UD^+) = 0.3183$ $d(D^+{}_6, LD^+) = 0.0262$

$d(D^+{}_7, UD^+) = 0.2617$ $d(D^+{}_7, LD^+) = 0.0856$

$d(D^+{}_8, UD^+) = 0.1366$ $d(D^+{}_8, LD^+) = 0.2026$ &

$d(D^-{}_1, UD^-) = 0.3325$ $d(D^-{}_1, LD^-) = 0.3790$

$d(D^-{}_2, UD^-) = 0.4694$ $d(D^-{}_2, LD^-) = 0.2412$

$d(D^-{}_3, UD^-) = 0.4019$ $d(D^-{}_3, LD^-) = 0.3159$

$d(D^-{}_4, UD^-) = 0.7103$ $d(D^-{}_4, LD^-) = 0.0$

$d(D^-{}_5, UD^-) = 0.2734$ $d(D^-{}_5, LD^-) = 0.4381$

$d(D^-{}_6, UD^-) = 0.1098$ $d(D^-{}_6, LD^-) = 0.6050$

$d(D^-{}_7, UD^-) = 0.0$ $d(D^-{}_7, LD^-) = 0.7103$

$d(D^-{}_8, UD^-) = 0.3949$ $d(D^-{}_8, LD^-) = 0.3187$

Step 8: From the previous distance values A_i^+ and A_i^- calculated by formula

$\boldsymbol{A_i^+ = d(D^+{}_i, LD^+) + d(D^-{}_i, UD^-)}$	$\boldsymbol{A_i^- = d(D^+{}_i, UD^+) + d(D^-{}_i, LD^-)}$
$\boldsymbol{A_1^+ = 0.3311 + 0.3325 = 0.6636}$	$A_1^- = 0.0 + 0.3790 = 0.3790$
$\boldsymbol{A_2^+ = 0.1597 + 0.4694 = 0.6291}$	$A_2^- = 0.1731 + 0.2412 = 0.4143$
$\boldsymbol{A_3^+ = 0.2317 + 0.4019 = 0.6336}$	$A_3^- = 0.1067 + 0.3159 = 0.4226$
$\boldsymbol{A_4^+ = 0.2513 + 0.7103 = 0.9616}$	$A_4^- = 0.0967 + 0.0 = 0.0967$
$\boldsymbol{A_5^+ = 0.1567 + 0.2734 = 0.4301}$	$A_5^- = 0.1890 + 0.4381 = 0.6271$
$\boldsymbol{A_6^+ = 0.0262 + 0.1098 = 0.1360}$	$A_6^- = 0.3183 + 0.6050 = 0.9233$
$\boldsymbol{A_7^+ = 0.0856 + 0.0000 = 0.0851}$	$A_7^- = 0.2617 + 0.7103 = 0.9720$
$\boldsymbol{A_8^+ = 0.2026 + 0.3949 = 0.5975}$	$A_8^- = 0.1366 + 0.3187 = 0.4553$

Table: 9 Calculations of Positive and Negative ideal solution

Step 9: Finally evaluated results are given by calculating $A_i^* = \frac{A_i^-}{A_i^- + A_i^+}$

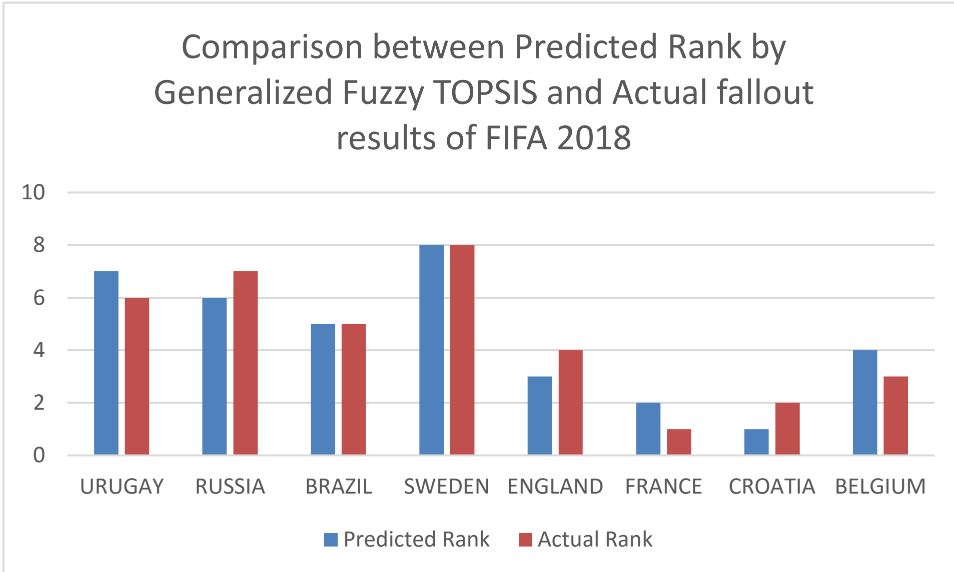
$A_1 = 0.3635$, $A_2 = 0.3971$, $A_3 = 0.4001$, $A_4 = 0.0914$,

$A_5 = 0.5932$, $A_6 = 0.8716$, $A_7 = 0.9191$, $A_8 = 0.4325$

Strategy	Final value	Predicted Rank	Actual Rank
$\boldsymbol{A_1}$	0.3635	7	6
$\boldsymbol{A_2}$	0.3971	6	7
$\boldsymbol{A_3}$	0.4001	5	5
$\boldsymbol{A_4}$	0.0914	8	8
$\boldsymbol{A_5}$	0.5932	3	4
$\boldsymbol{A_6}$	0.8716	2	1
$\boldsymbol{A_7}$	0.9191	1	2
$\boldsymbol{A_8}$	0.4325	4	3

Table: 10 Final result by Generalized Fuzzy TOPSIS vs Actual Rankings of the fallout of FIFA 2018

Clearly, $A_7 > A_6 > A_5 > A_8 > A_3 > A_2 > A_1 > A_4$, and the best performance is A_7 =Croatia.



Graph: 4 Comparison of Predicted Rank by Generalized Fuzzy TOPSIS and Actual fallout results of FIFA 2018

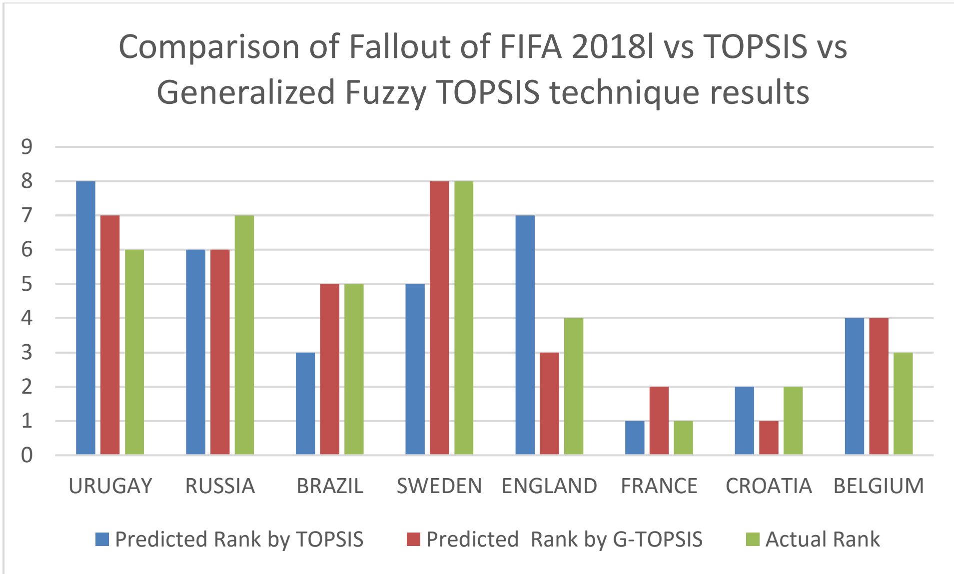
4. Result Discussion

The illustration of the game soccer and prediction of FIFA 2018 has been dealt with. As the stats of each team were neither the same nor closed. Thus, an MCDM (Multi-Criteria Decision Making) approaches, TOPSIS and Generalized Fuzzy TOPSIS are considered in the prediction model. The prediction model is based on alternatives which are teams and attributes of each team. The results have been shown in the table: 4, table: 10, graph:1 and graph:2 respectively.

	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8
PREDICTED RANK BY TOPSIS	8	6	3	5	7	1	2	4
PREDICTED RANK BY G-TOPSIS	7	6	5	8	3	2	1	4
ACTUAL RANK	6	7	5	8	4	1	2	3

Table: 11 Comparison of Fallout of FIFA 2018l vs TOPSIS vs Generalized Fuzzy TOPSIS technique results

In Table: 11 all the outcomes are shown. Results of Fuzzy TOPSIS shows that the alternative taken as A_1 have maximum chances to win FIFA 2018 which are quite different from the actual ranking of the fallout of FIFA but when we consider all the precise and vague values in term of Neutrosophic the predicted ranks are approximately the same if we consider more attribute true prediction can be done. To this end, an individual match chart displays individual measurements. The results have shown in the graph: 5.



Graph: 5 Comparison of Fallout of FIFA 2018l vs TOPSIS vs Generalized Fuzzy TOPSIS technique

5. Conclusion

The main purpose of this study was to predict the results for the rest of the matches of the FIFA 2018 world cup based on current match statistics till quarterfinals. It was a hard task to predict soccer match results since it was relying on several factors, such as weather conditions and players performance as well as various actors and unforeseen situations. So, such research requires the MCDM approach as this approach can calculate and predict taking various factors into consideration. In this research, the TOPSIS technique of MCDM and Generalized Fuzzy TOPSIS were applied to the statistics which have been collected from matches till quarterfinals. Both the mathematical techniques resulted in rankings of teams. After the fallout of FIFA 2018, the predicted results were compared with the actual rankings of the teams as in Table: 11. which showed that predicted results of generalized Fuzzy TOPSIS were approximately similar to the actual rankings. This research was limited to eight attributes which led us to the predicted results. In addition, predicting results can be more accurate by considering even more attributes. Therefore, the findings of this research are the application of both mathematical techniques. In the future, the application of these approaches can be used to predict the fallout of soccer matches as well as all those sports involving several factors in determining the results.

References

[1] Crowder, M., Dixon, M., Ledford, A. and Robinson, M. (2002), Dynamic Modelling and prediction of English Soccer League matches for betting, *Journal of the Royal Statistical Society: Series D (The Statistician)*, Vol. 51, No. 2, pp. 157-168.

[2] Dixon, M.J. and Coles, S.G. (1997), Modelling association soccer scores and inefficiencies in the soccer betting market, *Journal of the Royal Statistical Society: Series C (Applied Statistics)*, Vol. 46, No. 2, pp. 265-280.

[3] Falter, J.M. and Pérignon, C. (2000), Demand for soccer and intra match winning probability: an essay on the glorious uncertainty of sports, *Applied Economics*, Vol. 32, No. 13, pp. 1757-1765.

[4] Forrest, D. and Simmons, R. (2002), Outcome uncertainty and attendance demand in sport: the case of English soccer, *The Statistician,* Vol. 51, No. 2, pp. 291–241.

[5] Flitman, A.M. (2006), Towards probabilistic footy tipping: a hybrid approach utilizing genetically defined neural networks and linear programming, *Computers & operations research*, Vol. 33, No. 7, pp. 2003-2022.

[6] Goddard, J. and Asimakopoulos, I. (2004), Forecasting soccer results and the efficiency of fixed-odds betting, *Journal of Forecasting*, Vol. 23, No.1, pp51-66.

[7] Goddard, J. (2005), Regression models for forecasting goals and match results in association soccer, *International Journal of forecasting*, Vol. 21, No.2, pp. 331-340.

[8] Grunz, A., Memmert, D. and Perl, J. (2012)"Tactical pattern recognition in soccer games by means of special self-organizing maps", *Human movement science*, Vol.31, No. 2, pp. 334-343.

[9] Halicioglu, F. (2005), Can we predict the outcome of the international soccer tournaments: The Case of EURO 2000, *Dogus University Journal*, Vol. 6, No. 1, pp. 59–69.

[10] Halicioglu, F. (2005), forecasting *the professional team sporting events: evidence from Euro 2000 and 2004 soccer tournaments*, (No. 0508001), EconWPA.

[11] Hvattum, L.M. and Arntzen, H. (2010), Using ELO ratings for match result prediction in association soccer", *International Journal of forecasting*, Vol. 26, No. 3, pp. 460-470.

[12] Joseph, A., Fenton, N.E. and Neil, M. (2006), Predicting soccer results using Bayesian nets and other machine learning techniques, *Knowledge-Based Systems*, Vol. 19, No. 7, pp. 544-553.

[13] Karlis, D. and Ntzoufras, I. (1999) *On Modelling Association Soccer Data*, Technical Report, Department of Statistics, AUEB.

[14] Koning, R.H. (2000), Balance in competition in Dutch soccer, *Journal of the Royal Statistical Society: Series D (The Statistician),* Vol. 49, No. 3, pp. 419-431.

[15] Koning, R.H., Koolhaas, M., Renes, G. and Ridder, G. (2003), A Simulation Model for Soccer Championships, *European Journal of Operational Research*, Vol. 148, No. 2, pp. 268–276.

[16] Maji. P.K. (2013), Neutrosophic soft set, *Annals of Fuzzy Mathematics and Informatics*, Vol. 5, No.1 157-168.

[17] Min, B., Kim, J., Choe, C., Eom, H. and McKay, R.I. (2008), A compound framework for sports results prediction: A soccer case study, *Knowledge-Based Systems*, Vol. 21, No. 7, pp. 551-562.

[18] Rotshtein, A.P., Posner, M. and Rakityanskaya, A.B. (2005), Soccer predictions based on a fuzzy model with genetic and neural tuning, *Cybernetics and Systems Analysis*, Vol. 41, No. 4, pp. 619-630.

[19] Rue, H. and Salvesen, O. (2000), Prediction and retrospective analysis of soccer matches in a league, *Journal of the Royal Statistical Society: Series D (The Statistician)*, Vol. 49, No. 3, pp. 399-418.

[20] Saqlain. M., Jafar. N., Rashid. M. and Shahzad. A. (2019), Prediction of Cricket World Cup 2019 by TOPSIS Technique of MCDM-A Mathematical Analysis, *International Journal of Scientific & Engineering Research*, Vol. 10, No. 2, pp. 789-792.

[21] Smarandache. F. (2005), Neutrosophic set - a generalization of the intuitionistic fuzzy set, *International Journal of Pure and Applied Mathematics*, Vol. 24, No.3, pp 287–297.

[22] Yu-Jie Wang and Hsuan-Shih Lee (2007), Generalizing TOPSIS for fuzzy multiple-criteria group decision-making, *Computers and Mathematics with Applications*, Vol. 53, pp. 1762–1772.

[23] *Yoon, K.; Hwang, C.L.* (1981). *Multiple Attribute Decision Making: Methods and Applications. New York: Springer-Verlag.*