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Selection of dream-11 players in T20 cricket by using TOPSIS method

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A B S T R A C T

In terms of competitors, spectators, and media interest, cricket is one of the favorite international sports. At the international level, cricket may be played in three formats: a five-day Test, a one-day International (ODI) for each squad of 50 overs, and a Twenty-Twenty (T20) for each team of 20 overs. Various online games that are based on the aforementioned cricket forms allow players to form a virtual squad of real-life players and score points based on how well they perform in real matches. A user gains better rank on the leaderboard if they get the most points in all of the contests they have participated in. Dream11 is one such online gaming platform which offers free and paid contests and thereby gamers can win some cash rewards. So users can select the eleven players and form a team. These eleven players should be selected from the two teams between which the match will be played. Additionally, these eleven players may be chosen from either one team or a combination of the two teams. To identify the eleven players for the T20 cricket format who can provide the maximum score to get the best rank in competitions, many studies employ Multi Criteria Decision Making (MCDM).In this paper, the TOPSIS method is utilized (weights of the performance factors of players are evaluated by using AHP) to determine the top eleven players.

1. Introduction

Dream 11 is a famous online game that gives a superb platform for dynamic sports such as football, baseball, hockey, basketball, and many formats of cricket. In this game, a hypothetical team may be built based on the players who participate in the real-time game and earn points based on their performance and rank in the squad. The individual who receives the most points based on their competing contest scores is rated first. Free and paid competitions are available on Dream 11. To participate in Dream 11, users must be at least 18 years old and have a PAN (Permanent Account Number). To play in the game, the user must pay a participation fee based on the type of sport. TOPSIS was utilized in this study to choose Dream 11 players for the T20 cricket format using the Multi-Criteria Decision-Making (MCDM) algorithm. TOPSIS assists in providing priority to players that use the right technique to achieve top rankings. The following is a comprehensive literature review.

The majority of real-world decision-making difficulties need the simultaneous examination of several conflicting criteria and objectives. Compromise is required, for example, to strike a balance between a car's performance and cost, or between eating properly and enjoying life. Similar conflicts emerge in the selection of materials between material characteristics and performance measurements (Jahan, A et al., 2016). Materials selection is undoubtedly one of the most significant MCDM applications (along with software selection, project selection, and system selection). It is necessary to conduct a multi-criteria decision analysis due to the large number of competing attributes used in the selection of composites. Majority of researchers have

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utilized the technique TOPSIS for tackling the problem of material selection even though there are many different multi-criteria decision-making techniques available (Gireesh, C. H et al., 2019).
MCDM techniques are used in many other contexts apart from the above mentioned problems, especially in cricket to find out the rankings of the individual players and cricket teams by using available statistics. These techniques were used to compile the greatest World XI Test cricket squad ever, including over 2600 players who competed in Test matches during the course of the sport's more than 100-year existence. Containing the performances of numerous Test cricketers, each with a manageable number of candidate alternatives, while imposing some restrictions on batsmen based on the minimum number of matches played, wicket keepers and bowlers based on the minimum number of tests played, and all-rounders based on the minimum number of runs scored and wickets taken. The TOPSIS technique is then used to assess the cricketers who made the short list and decide which players would perform best in the projected World XI Test squad (Chakraborty, S et al., 2018).
Concerns have been expressed by sports officials, players, and fans about overseas player rankings for the IPL auction. When premium leagues are commercialized, these rankings will become increasingly important to investors. The Indian Premier League chooses players based on their own sporting experience as well as performance statistics on a variety of parameters. TOPSIS, TODIM, and NR-TOPSIS algorithms were used by Dutta, V et al., (2022) to rate players in the Indian Premier League. However, their analysis was confined to bowlers and batsmen. Selecting players for a strong cricket team on a limited budget is a difficult issue that may be understood as a constrained multi-objective optimization problem. The batting and bowling strengths of a team are the key aspects influencing its success in cricket team construction, and an optimal trade-off must be established in the formation of a strong team. Ahmed, F. et al. (2011) offered a multi-objective strategy based on the NSGA-II algorithm to maximize a team's total batting and bowling strength and choose team members for a strong team. A balanced cricket squad includes players with various abilities such as batting, bowling, all-rounder, and wicket keeper. Keeping these cricketing requirements in mind, drafting an optimal squad is a challenging task. The selectors choose cricketers based on their own knowledge and the recent performances of available players of all levels of competence. Saikia, H et al., (2016) proposed a method which can define players' performance into a single numerical number, which is a measure of the player's cricketing efficiency. To statistically explain the approach, data from the 2012 Indian Premier League (IPL) was utilized to identify game performances under varying levels of experience. To evaluate the approach, players picked in the real-time IPL 2012 season were compared to players selected using the algorithm, and it was discovered that many non-performers were chosen over performers in the main team. Kamble et al. (2011) suggested an algorithm for selecting players from a universal collection of cricketers based on their performance in batting, bowing, and fielding. Barr and Kantor (2004) suggested a new strategy to cricket player selection criteria. The authors examined batsman comparisons and selections in limited overs cricket. They accomplished this by adopting a two-dimensional graphical representation of the strike rate versus the probability of striking out. Irvine, S., and R. Kennedy (2017) investigated the performance measures that most strongly influence the result of an international T20 cricket game in various locations around the world. From 2012 to 2016, cricket-specific analysis software was utilized to analyse 40 international matches from seven distinct countries.

In contrast to the batsman's innings run rate, the performance of the bowler is mostly focused on the number of dot balls and wickets taken. This offers a strong selection of captain, wicket-taking bowlers, and batsmen with great strike rates and good boundary percentage. When compared to the real-time squad, the algorithms developed by Douglas and Tam (2010), Moore and Petersen (2002), and others were successful in attaining the highest targets during the final five overs. According to the above-mentioned reviewed literature, the use of MCDM approaches in the field of effective cricket team selection is extremely limited. It is also worth noting that no productive effort has been made till now to determine the best combination of the Dream 11 cricket team. As a result, there is enough flexibility to use any of the available multi-criteria decision making (MCDM) approaches to build the finest Dream 11 cricket squad for the T20 cricket format. In the face of numerous mutually incompatible attributes, an MCDM technique evaluates and identifies the optimum course of alternative. The problem that usually arises in my opinion is what would be the best form of a Dream 11 cricket team if all the participating and participating players are considered into account at the same time. Thus, the purpose of this paper is to select the best eleven players from the two sides between which the match will be played. The TOPSIS method, which has already been established as an optimal MCDM tool for tackling difficult decision making problems, is utilized in this study to identify the top eleven players from two teams (22 players) for the T20 cricket format.

2. TOPSIS (Technique for Order Preference by Similarity to Ideal Solution)

This study employs the technique for order preference by similarity to ideal solution (TOPSIS), to determine the ranks of 22 players from two teams. A detailed step by step procedure of this method is described below. Because it may make decisions on method selection, evolution, and prioritization, multi criteria decision making (MCDM) is well known. In 1981, Hwang and Yoon introduced a traditional MCDM strategy called TOPSIS, which allows for the prioritization of a specific order among similar ideal solutions. Priority is determined using Euclidean distances, which is highly helpful for sorting and choosing items from among many similar solutions. The chosen answer should be extremely close to the practical solution; it can be viewed as a positive solution. The remaining possibilities can be viewed as negative solutions because they are distant from the practical solution (Koona & Himagireesh, 2002). The ideal option that provides the best solution for all examined criteria is the positive solution.

Step 1: Developing a decision matrix

In a decision-making process with “n” alternatives (A) and "m" criteria (C), the decision matrix can be described as fallows and it is depicted in Table 1.

where A_i = the i^{th} alternative (i=1, 2,…, n)

C_j = the j^{th} criterion (j =1, 2,…, m)

x_{ij} = Rating based on individual performance.

Table 1
Decision matrix format

		Criteria (C)					
		Cr_1	Cr_2	Cr_3	…	…	Cr_m
Alternatives (A)	Al_1	X_{11}	X_{12}	X_{13}	…	…	X_{1m}
	Al_2	X_{21}	X_{22}	X_{23}	…	…	X_{2m}
	Al_3	X_{31}	X_{32}	X_{33}	…	…	X_{3m}
	…	…	…	…	…	…	…
	…	…	…	…	…	…	…
	Al_n	X_{n1}	X_{n2}	X_{n3}	…	…	X_{nm}

Step 2: Developing a normalized decision matrix

Calculating normalized evaluations using the formula below yields the normalized decision matrix.

$$r_{ij}\left(x\right)=\frac{x_{ij}}{\sqrt{\sum_{i=1}^{n}x_{ij}^{2}}} \tag{1}$$

Step 3: Decision matrix construction based on normalized weights.

Eq. (2) can be used to measure the initial weighted normalized ratings, which can be used to define the weighted normalized matrix.

$$v_{ij}\left(x\right)=w_j\left[r_{ij}\left(x\right)\right] \tag{2}$$

where w_j defines weightage of j^{th} criterion.

Step 4: Creating excellent solutions for both good and bad situations

The positive ideal solution V^+ and the negative ideal solution V^- are determined as follows:

$$V^+=\max\left\{v_1^+\left(x\right),v_2^+\left(x\right),,..,v_j^+\left(x\right)\right\},j=1,2,...m \tag{3}$$

$$V^-=\min\left\{v_1^-\left(x\right),v_2^-\left(x\right),,..,v_j^-\left(x\right)\right\},j=1,2,...m \tag{4}$$

Step 5: Separation measurements are calculated for each alternative.

Between the alternatives, distinguishing measures from the positive and negative ideal options are established. The following equation may be used to compute the separation (distances) of every possible solution from the positive ideal answer.

$$D_i^+=\sqrt{\sum_{j=1}^{m}\left\{\left[v_{ij}\left(x\right)-v_j^+\left(x\right)\right]\right\}^2} \tag{5}$$

Similarly, the following formula can be used to determine distance from negative solution to each alternative.

$$D_i^- = \sqrt{\sum_{j=1}^{m} \left\{ \left[v_{ij}(x) - v_j^-(x) \right] \right\}^2} \tag{6}$$

Step 6: Measurement of Closeness coefficient

The following expression is used to compute the closeness coefficients for all alternatives.

$$C_i^+ = \frac{D_i^-}{D_i^+ + D_i^-} \tag{7}$$

where $i = 1, 2, 3, \ldots\ldots n$

The closeness coefficient $\left(C_i^+\right)$ range between 0 and 1.

Step 7: Rank all the alternatives

The values of the closeness coefficients are necessary to rank the options.

Step 8: Decide on the finest alternatives.

The chosen alternative is the one with the highest closeness coefficient value (closest to 1).

3. Selection of eleven players for Dream 11for T20 cricket format from both the teams by proposed TOPSIS method

In this paper the best eleven players selected for the Dream11 team have been divided into batting, bowling and all-rounder categories. Total twenty two players from both the teams between which the match will be played are categorized in the above mentioned categories. The wicket keepers from both teams are considered under batting category. Among the best eleven players selected for the Dream11 team, five bowlers have been selected in the batting category, three players in the bowling category and three players in the all-rounder's category. So by including the players of the two competing teams, the ranks of ten players in the batting category, six players in the bowling category and 6 players in the all-rounder category are found by using the TOPSIS method. After finding ranks of players in the three categories top rankers from each category (top five rankers from batting category, top three rankers from bowling category and top three rankers from all-rounder category) are selected. The performance factors (Criterions) of the players in the three categories that are used in TOPSIS are presented in Table 2.

Table 2
Performance factors of categories

Category of Player	Performance Factor
Batting	No.of Matches **(NOM)**
	Average score**(AS)**
	Strike rate**(SR)**
	No.of 50s**(50s)**
Bowling	Total Runs given**(TRG)**
	No.of wickets taken**(NWT)**
	Economy**(ECO)**
	No.of Matches **(NOM)**
All-Rounder	Total Runs**(TR)**
	No.of 50s**(50s)**
	Total Runs given**(TRG)**
	No.of wickets taken**(NWT)**

It is clearly observed from Table 2 that the performance factors considered for batting category are Number of matches (NOM), Average score (AS), Strike rate(SR) and Number of 50s (50s) of a player and for bowling category Total Runs given (TRG), Number of wickets taken (NWT), Economy (ECO) and Number of matches. But in the All-rounder category total eight performance factors which are considered in batting and bowling categories and additionally Total runs performance factor is also considered.

The teams (TEAM-A and TEAM-B)between which the match will be played, the category of the player and the sample values of performance factors (data collected for the span 2007-2022 from ESPN CRICINFO) is presented in Table 3 and Table 4.

4. Evaluation of weights of performance factors

Performance measurements indicate multiple facets of a player's ability, thus some are more important than others. Batting average, for example, is a significant factor in all versions of the game since it demonstrates a batsman's ability to score runs in general. Similarly, strike rate is a crucial aspect in limited overs matches since it is important to score more runs. As a result, each measure of performance is weighted based on its relative value to other measures. The weights are obtained using the analytic hierarchy process (AHP) (Passi & Pandey, 2018; Saaty, 1977). AHP is a useful method for making complicated decisions. It assists in prioritizing and choosing the best choice. AHP simplifies complicated judgments by using pairwise comparisons. AHP considers both subjective and objective factors while making a judgment. Based on the decision maker's pairwise evaluations of the assessment criteria, AHP allocates a weight to each criterion. The greater the weight, the greater the importance of the relevant criterion. As per the procedure of AHP the subjective weights (α_j), objective weights (β_j) (obtained by Shannon entropy method (Shannon, 2001)) and synthesis weights (w_j) (which are obtained through (α_j) and (β_j)) are presented in Table 5, 6 and 7 for batting, bowling and all-rounder categories.

Table 3
Categories of the TEAM-A players and Values of Performance factors

Category of Player	TEAM-A (T-A)	NOM	AS	SR	50s	TR	TRG	NWT	ECO
Batting	T-A Player 1	148	31.32	139.24	29	---	---	---	---
	T-A Player 2	72	37.75	139.12	22	---	---	---	---
	T-A Player 3	115	52.73	137.96	37	---	---	---	---
	T-A Player 4	42	44.00	180.97	12	---	---	---	---
	T-A Player 5	66	22.43	126.37	3	---	---	---	---
Bowling	T-A Player 6	65	---	---	---	---	1672	72	6.9
	T-A Player 7	87	---	---	---	---	2079	90	6.96
	T-A Player 8	21	---	---	---	---	598	33	8.17
All-Rounder	T-A Player 9	---	---	---	1	302	45	5	---
	T-A Player 10	---	---	---	3	1160	1695	62	---
	T-A Player 11	---	---	---	1	171	855	34	---

Table 4
Categories of the TEAM-B players and Values of Performance factors

Category of Player	TEAM-B (T-B)	NOM	AS	SR	50s	TR	TRG	NWT	ECO
Batting	T-B Player 1	72	21.73	129.02	8	---	---	---	---
	T-B Player 2	99	41.41	127.8	30	---	---	---	---
	T-B Player 3	21	25.46	121.65	3	---	---	---	---
	T-B Player 4	124	31.21	125.64	9	---	---	---	---
	T-B Player 5	61	27.26	125.26	3	---	---	---	---
Bowling	T-B Player 6	36	---	---	---	---	971	34	8.2
	T-B Player 7	47	---	---	---	---	1298	58	7.52
	T-B Player 8	27	---	---	---	---	853	25	8.44
All-Rounder	T-B Player 9	---	---	---	14	2514	1388	61	---
	T-B Player 10	---	---	---	1	476	2105	98	---
	T-B Player 11	---	---	---	5	986	1957	44	---

Table 5
Subjective weights, objective weights and synthesis weights for batting category

Player selection criteria	Subjective weights obtained through AHP method (α_j)	Objective weights Obtained through Shannon entropy method (β_j)	Synthesis weights (w_j)	Priority order
No.of Matches	0.122	0.252	0.138	3
Average score	0.396	0.309	0.553	1
Strike rate	0.086	0.340	0.132	4
No.of 50s	0.396	0.098	0.176	2

Table 6
Subjective weights, objective weights and synthesis weights for bowling category

Player selection criteria	Subjective weights obtained through AHP method (α_j)	Objective weights Obtained through Shannon entropy method (β_j)	Synthesis weights (w_j)	Priority order
Total Runs given	0.243	0.234	0.262	2
No.of wickets taken	0.090	0.195	0.081	4
Economy	0.130	0.403	0.241	3
No.of Matches	0.537	0.168	0.416	1

Table 7
Subjective weights, objective weights and synthesis weights for all-rounder category

Player selection criteria	Subjective weights obtained through AHP method (α_j)	Objective weights Obtained through Shannon entropy method (β_j)	Synthesis weights (w_j)	Priority order
Total Runs	0.332	0.247	0.328	1
No.of 50s	0.235	0.227	0.214	3
Total Runs given	0.126	0.262	0.132	4
No.of wickets taken	0.308	0.264	0.326	2

The weightages of batting category derived by combining subjective and objective weights are then employed in TOPSIS approach to construct a weighted normalized matrix. As previously stated in step 3, the weighted normalized decision matrix is constructed and displayed below.

$$V_{ij} = \begin{bmatrix} 0.035 & 0.109 & 0.040 & 0.023 \\ 0.048 & 0.208 & 0.039 & 0.084 \\ 0.010 & 0.128 & 0.037 & 0.008 \\ 0.060 & 0.156 & 0.038 & 0.025 \\ 0.030 & 0.137 & 0.038 & 0.008 \\ 0.072 & 0.157 & 0.043 & 0.082 \\ 0.035 & 0.189 & 0.043 & 0.062 \\ 0.056 & 0.264 & 0.042 & 0.104 \\ 0.020 & 0.220 & 0.055 & 0.034 \\ 0.032 & 0.112 & 0.039 & 0.008 \end{bmatrix}$$

Step 4 uses the two techniques—larger is better and smaller is better—to obtain the positive ideal solution (PIS) and negative ideal solution (NIS). Following is a description of the PIS and NIS. $V^{+} = \{0.010 \quad 0.264 \quad 0.055 \quad 0.104\}$

$V^{-} = \{0.072 \quad 0.109 \quad 0.037 \quad 0.008\}$

The separation measurements, i.e., the distance of each alternate (PLAYER) from the positive and negative ideal solutions, as well as the closeness coefficients for all players, are determined using the process described in step 5 of the TOPSIS methodology. For example, the computation of the T-A PLAYER 1's separation measures and closeness coefficients is shown below.

$$D_i^{+} = \sqrt{(0.010-0.035)^2 + \left(0.264-0.109\right)^2 + (0.055-0.040)^2 + (0.104-0.023)^2} = 0.178$$

$$D_i^{-} = \sqrt{(0.035-0.072)^2 + \left(0.109-0.109\right)^2 + (0.040-0.037)^2 + (0.023-0.008)^2} = 0.040$$

$$C_i^{+} = \frac{0.040}{0.178+0.040} = 0.182$$

Similar to this, all remaining players in the batting category had their separation measures and closeness coefficients calculated. Table 8 displays the priority ranks of all players, and Tables 9 and 10 show the separation measures and closeness coefficients for the bowling category and all-rounder category, respectively.

Table 8
Separation measures, Closeness coefficients and Ranks of batting category players

Player	Separation measures		Closeness coefficient (C_i^+)	Rank
	D_i^+	D_i^-		
T-A PLAYER 1	0.178	0.040	0.182	9
T-A PLAYER 2	0.073	0.127	0.635	2
T-A PLAYER 3	0.168	0.064	0.277	6
T-A PLAYER 4	0.144	0.052	0.265	7
T-A PLAYER 5	0.162	0.050	0.238	8
T-B PLAYER 1	0.126	0.088	0.410	5
T-B PLAYER 2	0.091	0.103	0.533	4
T-B PLAYER 3	0.047	0.183	0.794	1
T-B PLAYER 4	0.083	0.127	0.603	3
T-B PLAYER 5	0.182	0.040	0.180	10

Table 9
Separation measures, Closeness coefficients and Ranks of bowling category players

Player	Separation measures		Closeness coefficient (C_i^+)	Rank
	D_i^+	D_i^-		
T-A PLAYER 6	0.104	0.190	0.646	2
T-A PLAYER 7	0.110	0.257	0.701	1
T-A PLAYER 8	0.226	0.114	0.336	4
T-B PLAYER 6	0.223	0.091	0.290	5
T-B PLAYER 7	0.135	0.146	0.519	3
T-B PLAYER 8	0.258	0.097	0.273	6

Table 10
Separation measures, Closeness coefficients and Ranks of All-Rounder category players

Player	Separation measures		Closeness coefficient (C_i^+)	Rank
	D_i^+	D_i^-		
T-A PLAYER 9	0.471	0.170	0.265	3
T-A PLAYER 10	0.411	0.106	0.206	5
T-A PLAYER 11	0.473	0.141	0.229	4
T-B PLAYER 9	0.137	0.474	0.776	1
T-B PLAYER 10	0.490	0.094	0.161	6
T-B PLAYER 11	0.339	0.174	0.340	2

As per the ranks obtained in three categories the final selection of players for Dream-11 is presented in the Table 11. Among the three categories 5 players from batting category (including wicket keeper) 3 players from bowling category and 3 players from all-rounder category are considered on the base of their obtained ranks.

Table 11
Selected players for Dream-11 based on their Rank order

S.No	Category of the Player	Name of the Player	Rank obtained
1	Batting	T-B Player 3	1
2		T-A Player 2	2
3		T-B Player 4	3
4		T-B Player 2	4
5		T-A Player 5 (WK)	8
6	Bowling	T-A Player 7	1
7		T-A Player 6	2
8		T-B Player 7	3
9	All-Rounder	T-B Player 9	1
10		T-B Player 11	2
11		T-A Player 9	3

5. Conclusion

The MCDM technique TOPSIS is utilized to identify the best eleven players for Dream 11 contest among Team-A and Team-B in batting (including wicket keeper), bowling and all-rounder categories with the help of AHP and Shannon entropy method (for finding subjective and objective weightages). Few remarkable conclusions in the study are

- In the batting category among the ten players 1 player from Team A (Team-A Player 2 with rank 2) and 4 players from Team-B (Team-B Player 1,2,3,4 with ranks 5,4,1,3 respectively) are identified as top 5 batting performers.
- Even though Team-B Player 1 attained Rank 5, his name would not be in the final list because the fifth player of batting category should be a wicket keeper. Among the two keepers Team-A Player 5 (8^{th} rank) obtain a best rank than Team-B Player 5(10^{th} rank). So Team-A Player 5 occupied the fifth position of final players of batting category.
- Among the six players three from Team-A and three from Team-B, Team-A Player 6, 7 and Team-B Player 7 has occupied place in the final list of bowling categories with rank 2, 1 and 3 respectively.
- In the all-Rounder category out of six players (3 from Team-A and 3 form Team-B) Player 9 from Team-A and Players 9 and 11 from Team-B occupied the best three positions with ranks obtained 3, 1, 2 respectively.

The top T20 and One-Day cricket teams in history can be chosen using the TOPSIS approach. It may be used to realistically choose the ideal player lineup for any multiplayer game played in any nation.

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