Neutrosophic MCDM Approach for Performance Evaluation and Recommendation of Best Players in Sports League

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Abstract

In this era of the commercialization of sports, various sports leagues are organized across the globe. At the end of the Series, players are awarded for their performances. These awards are decided by human experts or are based on just one performance indicator. However, human decisions are subjective and error-prone, and decisions based on just one criterion are incomplete and inconsistent. This paper identifies the decision-making problem in sports. It proposes a Neutrosophic TOPSIS approach for performance evaluation and recommendation of the best batsman and bowler of the Series. The approach is well-structured, robust, and efficient in handling vagueness, inconsistency, indeterminacy, and imprecision in real-life problems. We present a case study using the data of IPL 2021. In the case study, we calculate the ranks of the players using neutrosophic TOPSIS with two objective weight calculation methods. Then we evaluate and compare the obtained rank lists using Kendal Tau (τ). The values of τ for bowling-ranked lists is 0.83 and for batting-ranked lists is 0.72, which are impressive and prove the efficiency and effectiveness of the proposed approach. We believe that the proposed approach can be applied to identify and recommend the best resources in other domains of life.

Keywords: Neutrosophic MCDM; Cricket; Performance Evaluation; TOPSIS; Player

1. Introduction

In recent years, the commercialization of sports has presented lucrative career opportunities for sports persons. Many commercial leagues of different sports are organized across the world. The commercial leagues are managed by professionals who are required to make decisions in various situations and frame rules for the smooth functioning of the event [1]. Performance evaluation and ranking of players in a sports event is a multi-criteria decision-making (MCDM) problem. It is the task of evaluating players' impact in the match or the Series by analyzing their performance. MCDM is a systematic and organized decision-making process for addressing complex situations with conflicting criteria [2].

TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) is an extensively used MCDM technique in various real-life decision-making problems [3]. One of the main advantages of using TOPSIS for MCDM is that; it considers the conflicting nature of decision criteria and quickly identifies the best alternative [4]. Though TOPSIS has proved to be significant in dealing with real-life decision-making problems, it has a specific set of limitations while dealing with the uncertainty of events. It is evident that real-life problems always have some degree of uncertainty. The uncertain conditions compel researchers to monitor and manage the error caused by uncertainty [5]. Classical

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TOPSIS can evaluate the performance and rank the alternatives, but it cannot handle imprecise and vague information. The use of fuzzy TOPSIS can solve the problem of vague and imprecise information present in real-life decision-making problems [6]. The advancements in applying fuzzy set theory have increased the demand for advanced research in this field. The shortcomings of fuzzy set theory led to the development of numerous similar models, the most popular of which are the interval-valued fuzzy set [7], the intuitionistic fuzzy set [8], the interval-valued intuitionistic fuzzy set [9], the hesitant fuzzy set [10], the vague set [11], the neutrosophic set [12].

Smarandache introduced neutrosophic Sets (NS) to handle the inconsistency and indeterminacy of real-life situations [12]. NS is a generalization of the crisp set, fuzzy set, intuitionistic fuzzy set, and interval-valued fuzzy set [13]. Three membership functions characterize NS. The membership functions in NS accept the values in the non-standard interval]0-,1+[. NS are difficult to apply in engineering and real-life applications due to the non-standard interval of membership functions. In order to overcome the limitations of NS, Single valued Neutrosophic Sets (SVNS) were introduced [14]. SVN is a special type of Neutrosophic Set in which the values of membership functions are in the standard interval [0, 1]. SVN is used in various real-life problems to combat inconsistency, imprecision, incompleteness, and uncertainty in information [15] [16]. This paper aims to explore the application of TOPSIS under a neutrosophic environment by utilizing the potential of SVNS. In this direction, we develop an efficient decision-making model for performance evaluation and recommendation of the best players in sports. For this purpose, we have considered cricket as a case study in this work.

Cricket is one of the popular sports in many countries around the world. The inception of T-20 cricket has paved the way for the commercialization of cricket. In order to boost the morale of the best-performing players and to motivate other players to better performance, the organizers give various awards at the end of a match and Series, like the best batsman, the best bowler, and the best fielder, etc. Human experts decide these awards, or they are based on just one criterion, like the number of runs for the best batsman. These decision processes are not efficient, and various experts raise their concerns from time to time. Recommending the best player based on any one criteria is just one part of a large puzzle while evaluating the player performance and recommendation of the best player by the human expert is error-prone due to imprecision, indeterminacy, subjectivity, and vagueness in human decision-making. These limitations of the existing approaches motivated us for this study.

In this paper, we propose an intelligent framework that utilizes TOPSIS under a single-valued neutrosophic environment to evaluate the performance and recommend the best player in the sports league. The main contribution of the paper can be summarised as follows:

- A framework is proposed that evaluates the performance and recommends the best players in a sports league using the neutrosophic MCDM approach.
- A systematic approach is proposed for selecting the important features and for converting the crisp data into SVN.
- Neutrosophic TOPSIS for performance evaluation and ranking is used to combat vagueness, indeterminacy, inconsistency, and subjectivity in decision-making.
- A case study using the data of cricket is presented in which two different objective weights are used to compute the rank lists using neutrosophy.
- The evaluation of the obtained rank lists with Kendall Tau proves the consistency and effectiveness of the proposed approach.

The rest of the paper is organized as follows: In section 2, we present some of the preliminaries and related works. Section 3 discusses the proposed framework. Section 4 presents the illustrative case study along with the obtained results. Section 5 discusses the advantage of the proposed work, Section 6 presents the limitations and future directions, and the conclusion of the study is presented in section 7.

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2. Preliminaries and Related Works

In this section, we present a brief overview of the neutrosophic set, single-valued neutrosophic set, TOPSIS, Objective weight calculation methods, namely; CRITIC weights and entropy weights, evaluation measure Kendall tau and literature review related to our proposed work.

2.1. Neutrosophic Set

A Neutrosophic set (NS) is the generalization of the fuzzy set, intuitionistic fuzzy set, and interval-valued fuzzy set that has three membership functions. The membership functions are truth membership functions ($T_n(x)$), indeterminacy membership function ($I_n(x)$), and falsity membership function ($F_n(x)$). Mathematically NS can be defined as N in X, where X is the space of points [12].

N= $\{(x,\ T_n(x),\ I_n(x),\ F_n(x) : x\ \mathcal{E}\ X\ )\}$ and satisfies the following properties

$$T_n(x), \qquad I_n(x),\ F_n(x): X \to]0^-, 1^+[$$

$$0^- \le T_n(x) + I_n(x) + F_n(x) \le 3^+$$

2.2. Single-Valued Neutrosophic Set

A single-valued Neutrosophic set (SVNS) is a subset of the Neutrosophic set. It is used for various real-life applications in the domain of science, engineering, medicine, and operation research. It was developed to overcome the limitations of NS. The membership functions of SVNS satisfy the following constraints [14].

$T_n(x),\ I_n(x),\ F_n(x): X \to [0,1]$ For every $x\ \mathcal{E}$ X.

$$0 \le T_n(x) + I_n(x) + F_n(x) \le 3$$

2.3. TOPSIS

TOPSIS is one of the frequently used MCDM approaches, which gives the best alternative based on the distance between positive ideal and negative ideal solutions. The best alternative suggested by TOPSIS has a minimum distance from the positive ideal solution and a maximum distance from the negative ideal solution. TOPSIS is used by various researchers to solve a wide range of real-life MCDM problems [17]. The steps for ranking and recommending the best alternative using TOPSIS are as follows:

- Identify cost and benefit criteria.
- Find the best ideal solution and worst ideal solution for each criterion.
- Compute the distance of alternatives from ideal solutions.
- Compute the relative closeness of ideal solutions and rank the alternatives.

2.4. Methods for Weight Calculation

In MCDM problems, the weights of the criteria define the importance of the criteria. Weighting methods can be broadly classified into subjective and objective. Subjective weights are based on the DM's experience, whereas the objective weights are calculated based on the data of the decision problem [18]. CRITIC and entropy methods are popular methods for calculating objective weights.

A. CRITIC Weights

Criteria importance through inter-criteria correlation (CRITIC) is one of the techniques used to calculate the objective weights of the criteria. It is based on the correlation between different criteria and the standard deviation (SD) of the criteria of the decision problem. This method is proposed by [19]. The steps to calculate the CRITIC weights are as follows:

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- **Identify the cost and benefit criteria and normalize them using the following equations.**

For cost criteria

$$r_{ij} = \frac{\max(x_j)-x_{ij}}{\max(x_j)-\min(x_j)} \quad (1)$$

For benefit criteria

$$r_{ij} = \frac{x_{ij}-\min(x_j)}{\max(x_j)-min(x_j)} \quad (2)$$

where i = 1,…, m and j = 1,…, n

- **The correlation between different criteria is calculated using the equation.**

$$E_{ij} = \frac{\sum_{i=1}^{m}(r_{ij}-\bar{r}_j)(r_{ik}-\bar{r}_k)}{\sqrt[2]{\sum_{i=1}^{m}(r_{ij}-\bar{r}_j)^2 \sum_{i=1}^{m}(r_{ik}-\bar{r}_k)^2}} \quad (3)$$

where $j, k = 1, \ldots\ldots, n$

- **Calculate the standard deviation of each criterion using the following equation.**

$$\sigma_j = \sqrt[2]{\frac{(r_{ij}-r_j)^2}{n}} \quad (4)$$

- **Calculate the amount of information C_j contained in the jth criteria.**

$$c_j = \sigma_j \sum_{k=1}^{n}(1 - E_{jk}) \quad (5)$$

where $j = 1, \ldots\ldots\ldots, n$ and σ_j is the standard deviation of jth criteria.

- **The weights of the criteria are calculated using the following equation.**

$$W_j = \frac{c_j}{\sum_{k}^{n} k_k} \quad (6)$$

where $j = 1, \ldots\ldots\ldots, n$

B. Entropy Weights

This is one of the popular methods used to calculate the objective weights of the criteria [20]. For m alternatives and n criteria in a multi-criteria decision matrix. The value of an instance of the i^{th} alternative and the j^{th} criteria is represented as y_{ij}. The steps to calculate entropy weights are as follows:

- **Standardize the values by using the following equation.**

$$s_{ij} = \frac{y_{ij}}{\sum y_{ij}} \quad (7)$$

- **Calculate the entropy value of the j^{th} by using the following equation.**

$$E_j = -\frac{\sum s_{ij} \ln s_{ij}}{\ln m} \quad (8)$$

In the actual assessment using the Entropy method, if $s_{ij} = 0$, then for the convenience of calculation, we set $s_{ij}\ ln\, s_{ij}$ = 0. Where, $E_j \varepsilon$ [0,1]

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- **After calculating the entropy value, the weights of the criteria using the following equation.**

$$W_j = \frac{1 - E_j}{\sum(1 - E_j)} \tag{9}$$

2.5. Kendall Tau

The Kendall-Tau correlation coefficient measures the degree of agreement between two columns of ranking data [21]. In other words, Kendall's correlation coefficient analyses observations in pairs and evaluates the association's strength based on the concordance and discordance between the pairs. If r_1 and r_2 are two ranked lists, NC and n_d are the degrees of concordance and discordance between the ranked list. Then Kendall tau (τ) between the given ranked lists is calculated using the following equation.

$$\tau = \frac{n_c - n_d}{n_c + n_d} \tag{10}$$

where $\tau\ \mathcal{E}[-1,1]$, and satisfy the following properties.

τ=1, if the degree of association between the given ranked lists is perfect.

τ=-1, if the ranked lists are in complete disagreement with each other.

τ=0, if the ranked lists are independent of each other.

2.6. Related Work

In the last few years, many people have tried to automate the process of decision-making in various sports [22], like player selection, performance analysis [23], ranking of players, and team formation and winner prediction. For example, Tavana et al. [24] proposed a fuzzy-based two-stage framework for player selection and team formation for soccer. In the first phase, the fuzzy ranking method was used to evaluate the alternatives and select the top performers. In the second phase, alternative combinations were evaluated using a fuzzy inference system (FIS), and the best combination was selected.

Jayanth et al. [25] proposed a team recommender system that recommends the team combination for a specific opponent and a player for a specific role. The system uses supervised machine learning models with linear and non-linear RBF kernels and predicts the outcome of a match by grouping the players at different levels. The ranking index of players was calculated using player and team statistics extracted from a specific series, and players were grouped using the k-mean clustering technique.

Oukil & Govindaluri [26] introduced a method for ranking football players by integrating Data Envelopment Analysis (DEA) and Ordered weighted averaging (OWA) operators. The proposed approach was tested to rank the football players from European Premier League by considering their objective performance measures. Different levels of optimism of the decision-maker were used to evaluate the robustness of the proposed approach. The use of the OWA operator in human resource selection in sports management is analyzed in [27]. They parameterized the decision-making technique and used the adequacy coefficient, the Hamming distance, and the index of maximum and minimum levels.

Amin & Sharma [28] proposed a two-stage method for measuring the performance and ranking the parameters in T-20 cricket. In the first stage, OWA is used to measure the batting performance of the players, and in the second stage, different batting parameters are ranked using regression. The limitation of this work is that it considers only a few parameters for measuring performance. Anwar et al. [29] proposed an OWA-based feature extraction and ranking approach for the performance evaluation of cricket players. They considered five important batting features, calculated the weights of the features using the fuzzy linguistic quantifiers, and applied OWA for performance evaluation

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and ranking of players. They have reduced the subjectivity involved in the ranking and decision-making process by following a systematic approach for feature selection, data pre-processing, and player score calculation.

Ahmed et al. [30] explored the problem of selecting the best and high-performing team of eleven players from a given group of players. They analyzed the statistics of the past performance of players and used NSGA-II, which is an evolutionary multi-objective optimization algorithm to optimize the overall strength of the team, considering eleven players as variables.

The above studies signify the importance and applications of various MCDM techniques used in sports science. In the above literature, MCDM techniques are used for team formation in different sports by evaluating the player's performance. There are other decision-making situations in sports, like the selection of the best player of the match or the best player of the Series. The current literature lacks a study that automates the process to evaluate performance and recommend the best player in the league. In this direction, this paper proposes a framework for performance evaluation and recommendation of the best players in sports. The steps of the proposed framework are discussed in the subsequent section.

3. Proposed Framework

The proposed framework to identify and recommend the best player of the Series is given in figure 1. The framework consists of various steps. In the first step, it collects the data from the web, selects and extracts important features from the data, identifies the cost and benefit features, and normalizes the features. After normalization, weights of the selected features are calculated, crisp data is converted to SVN, and a neutrosophic decision matrix is formed. In the final step, neutrosophic TOPSIS is applied to identify and recommend the best player. Different steps of the framework are discussed below.

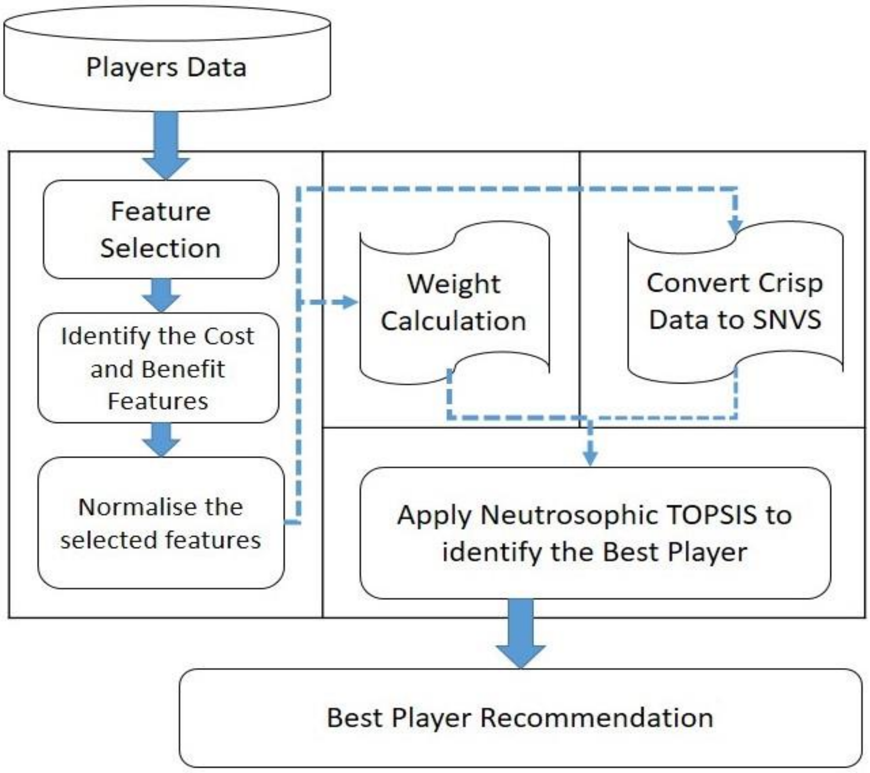

Figure 1: General Framework to identify and recommend the best player of the Series

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3.1. Data Collection

The first step of our framework is data collection and pre-processing. The data need to be authentic, verifiable, and collected from reliable sources on the web. The data should be converted to the proper format and cleaned to eliminate the noise and improve the effectiveness of the proposed framework. In this paper, the data is collected from authentic web sources.

3.2. Feature Selection and Extraction

The collected data have various attributes and features which may be redundant. In order to reduce the redundancy and computational cost, important features from the data are selected, and some features are combined to extract more informative features. A number of feature selection approaches, such as expert opinion, univariate, multivariate, and recursive elimination, are used by various researchers [31]. In this paper, we use expert opinion to select important features.

3.3. Identify the Cost and the Benefit Criteria

One of the important characteristics of the TOPSIS technique is the identification of cost and benefit criteria. The feature for which the maximum value is required is called benefit criteria, and the feature whose minimum value is favored is known as cost criteria. The proposed framework identifies the cost and benefit features.

3.4. Convert the Crisp Data into Single Valued Neutrosophic Set

The data that shows the performance of the players has crisp values. The crisp data need to be converted to neutrosophic data (Table 4, 9). In this paper, the data is converted into SNVS using the process suggested in [32]. Various steps to convert the crisp data into SNVS are shown in figure 2. The steps are data collection, feature selection, identification of cost and benefit criteria, normalizing the data, and conversion into SVN.

The data is normalized using the following equations.

For cost criteria

$$r_{ij} = \frac{\max(x_j) - x_{ij}}{\max(x_j) - \min(x_j)} \tag{11}$$

For benefit criteria

$$r_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - min(x_j)} \tag{12}$$

where $i = 1, \dots\dots, m$ and $j = 1, \dots\dots, n$

The crisp normalized values are converted to SVNNs using the following equations.

For benefit criteria,

$$(T_n, I_n, F_n) = (r_{ij}, 1 - r_{ij}, 1 - r_{ij}) \tag{13}$$

For cost criteria,

$$(T_n, I_n, F_n) = (1 - r_{ij}, r_{ij}, r_{ij}) \tag{14}$$

Figure 2: Steps to convert crisp data to SNVS

3.5. Calculate the Weights of the Criteria

The weights of different attributes are calculated using the objective weight calculation method discussed in section 2.4.

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3.6. Apply Neutrosophic TOPSIS

Neutrosophic TOPSIS is an efficient MCDM approach to handle indeterminacy, vagueness, and inconsistency. The final step of our proposed framework is the application of neutrosophic TOPSIS for performance evaluation and ranking. Figure 3 represents the flow diagram of neutrosophic TOPSIS. Various steps of the approach are:

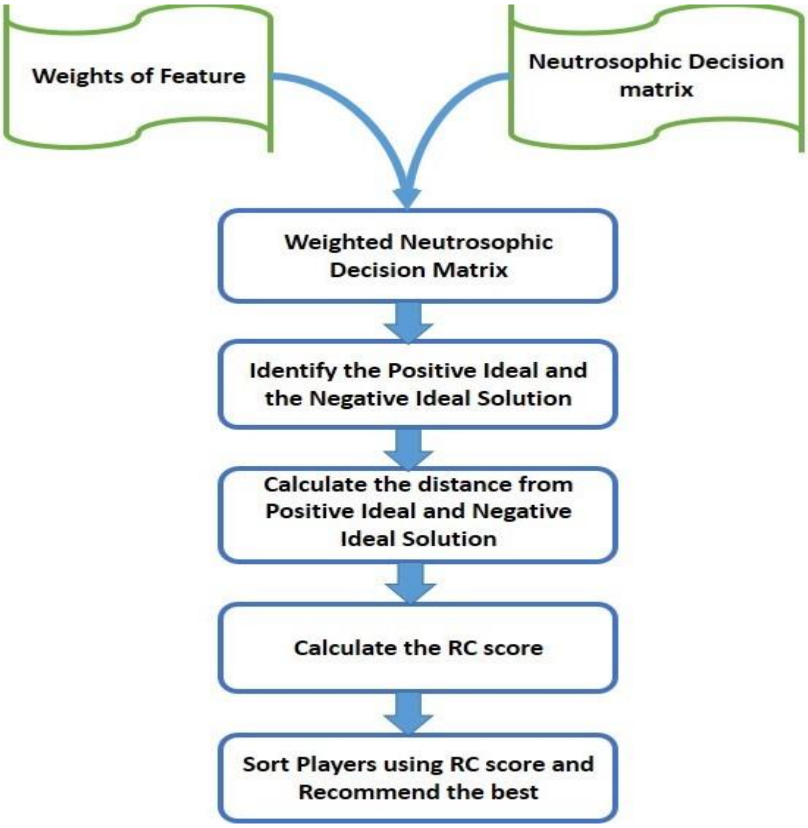

Figure 3: Flow Diagram for neutrosophic TOPSIS

- **Construct the Neutrosophic Decision Matrix**

The SVN can be presented in the form of the following decision matrix.

$$D = \left(d_{ij}\right)_{m\,X\,n} = \begin{bmatrix} d_{11} & d_{12} & \cdots & d_{1n} \\ d_{21} & \vdots & \cdots & \vdots \\ \cdots & \cdots & \cdots & \vdots \\ d_{m1} & \cdots & \cdots & d_{mn} \end{bmatrix} \qquad (15)$$

Where each entry of the decision matrix $d_{ij} = (T_{ij}, I_{ij}, F_{ij})$ represents the degree of truth, indeterminacy, and falsity, respectively, such that T_{ij}, I_{ij}, F_{ij} Ɛ [0,1]

- **Construct Weighted Single Valued Neutrosophic Decision Matrix**

The SVN weighted decision matrix is constructed and presented using the following equation.

$$D \otimes W = [d_{ij}{}^{w_j}]_{mXn} = \begin{bmatrix} d_{11}{}^{w_1} & d_{12}{}^{w_2} & \cdots & d_{1n}{}^{w_n} \\ d_{21}{}^{w_1} & \vdots & \cdots & \vdots \\ \vdots & \cdots & \cdots & \vdots \\ d_{m1}{}^{w_1} & \cdots & \cdots & d_{mn}{}^{w_n} \end{bmatrix} \begin{bmatrix} d_{11}{}^{w_1} & \cdots & d_{1n}{}^{w_n} \\ \vdots & \ddots & \vdots \\ d_{m1}{}^{w_1} & \cdots & d_{mn}{}^{w_n} \end{bmatrix} \qquad (16)$$

where $d_{ij}{}^{w_j} = < T_{ij}{}^{w_j}, I_{ij}{}^{w_j}, F_{ij}{}^{w_j} > = < 1 - (1 - T_{ij})^{w_j},\ I_{ij}{}^{w_j},\ F_{ij}{}^{w_j} >$

Doi : https://doi.org/10.54216/IJNS.200111
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- **Determine the Relative Positive Ideal Solution (RPIS) and Relative Negative Ideal Solution (RNIS) for SVNS's**

The relative positive ideal solution and relative negative ideal solution from SVNN are calculated by using the following equations.

For beneficial attributes

$$RPIS = < T_j^{w_j+}, I_j^{w_j+}, F_j^{w_j+} > = < \max(T_{ij}^{w_j}), \min(I_{ij}^{w_j}), \min(F_{ij}^{w_j}) > \quad (17)$$

$$RNIS = < T_j^{w_j-}, I_j^{w_j-}, F_j^{w_j-} > = < \min(T_{ij}^{w_j}), \max(I_{ij}^{w_j}), \max(F_{ij}^{w_j}) > \quad (18)$$

For cost attributes

$$RPIS = < T_j^{w_j+}, I_j^{w_j+}, F_j^{w_j+} > = < min(T_{ij}^{w_j}), max(I_{ij}^{w_j}), max(F_{ij}^{w_j}) > \quad (19)$$

$$RNIS = < T_j^{w_j-}, I_j^{w_j-}, F_j^{w_j-} > = < max(T_{ij}^{w_j}), min(I_{ij}^{w_j}), min(F_{ij}^{w_j}) > \quad (20)$$

- **Calculate the Distance of each Alternative from RPIS and RNIS for SVNSs**

The distance of each alternative $< T_{ij}^{w_j}, I_{ij}^{w_j}, F_{ij}^{w_j} >$ from RPIS $< T_j^{w_j+}, I_j^{w_j+}, F_j^{w_j+} >$ and from RNIS $< T_j^{w_j-}, I_j^{w_j-}, F_j^{w_j-} >$ is calculated using normalized Euclidian distance using the following equations.

$$Dis^{+} = \sqrt[2]{\frac{\sum_{j=i}^{n}\{\left(T_{ij}^{w_j} - T_j^{w_j+}\right)^2 + \left(I_{ij}^{w_j} - I_j^{w_j+}\right)^2 + \left(F_{ij}^{w_j} - F_j^{w_j+}\right)^2\}}{3n}} \quad (21)$$

$$Dis^{-} = \sqrt[2]{\frac{\sum_{j=i}^{n}\{(T_{ij}^{w_j} - T_j^{w_j-})^2 + (I_{ij}^{w_j} - I_j^{w_j-})^2 + (F_{ij}^{w_j} - F_j^{w_j-})^2\}}{3n}} \quad (22)$$

- **Calculate the Relative Closeness (RC) to the Neutrosophic Ideal Solution for SVNSs**

The relative closeness from the ideal solution is calculated using the following equation.

$$RC = \frac{Dis^{-}}{Dis^{-} + Dis^{+}} \quad (23)$$

- **Arrange the Alternatives and Recommend the Best Alternative**

The final step in neutrosophic TOPSIS is to arrange the alternatives according to the descending order of RC and rank the alternatives. The alternative having maximum value is recommended as the best one.

4. Illustrative Case Study

The proposed approach to recommend the best player is illustrated with the real data obtained from the Indian Premier League (IPL) 2021. IPL is one of the commercial cricket events organized by the Board of control for cricket in India. IPL provides a lucrative career opportunity for many cricketers across the world. After the final match, various players are awarded for their performance, such as the orange cap for the best batsman and the purple cap for the best bowler. The selection of the best bowler and the best batsman is based on the number of wickets and the number of runs, respectively. Recommending the best player based on just one feature is one part of a large puzzle. There are various other performance indication features that may be used to measure the performance of the players. The transparency in performance measurement and award distribution will motivate the players to improve their skills and perform well. We have applied the proposed approach to recommend the best batsman and the best bowler of the Series.

4.1. Use Case 1: Recommending the Best Batsman

The proposed framework to recommend the best player of the Series consists of various steps like data collection, feature selection, identification of cost and benefit features, calculating the objective

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weights of the features, and using neutrosophic TOPSIS to evaluate the performance and recommend the best player. For this case study, we collected the data of batsmen of IPL 2021. A few instances of the data obtained to measure the batting performance are given in Table 1. Other steps of the proposed framework are discussed below.

Table 1: Few instances of data obtained to measure batting performance

Player	Mat	Inns	NO	Runs	HS	Ave	BF	SR	100	50	0	4s	6s
RD Gaikwad	16	16	2	635	101*	45.35	466	136.26	1	4	0	64	23
F du Plessis	16	16	2	633	95*	45.21	458	138.20	0	6	2	60	23
KL Rahul	13	13	3	626	98*	62.60	451	138.80	0	6	0	48	30
S Dhawan	16	16	1	587	92	39.13	471	124.62	0	3	0	63	16
GJ Maxwell	15	14	2	513	78	42.75	356	144.10	0	6	1	48	21

A. Feature Selection

There are various features that indicate the performance of the players. Feature selection is an important factor that decides the performance of any evaluation model [33]. In this work, we have selected six different features to evaluate the batting performance and recommend the best batsman of the Series. The features selected in this paper are used by experts for performance evaluation. In the past, many researchers proposed solutions to evaluate the performance of batsmen and rank them. The main drawback of the previous research is that they considered very few features. The feature selected for performance evaluation in this paper are very important and have a high correlation with performance. A comparison of features selected in other studies and in our work is presented in Table 2. Figure 4 represents the features considered to measure batting performance. All six features are benefit features. The features are discussed below.

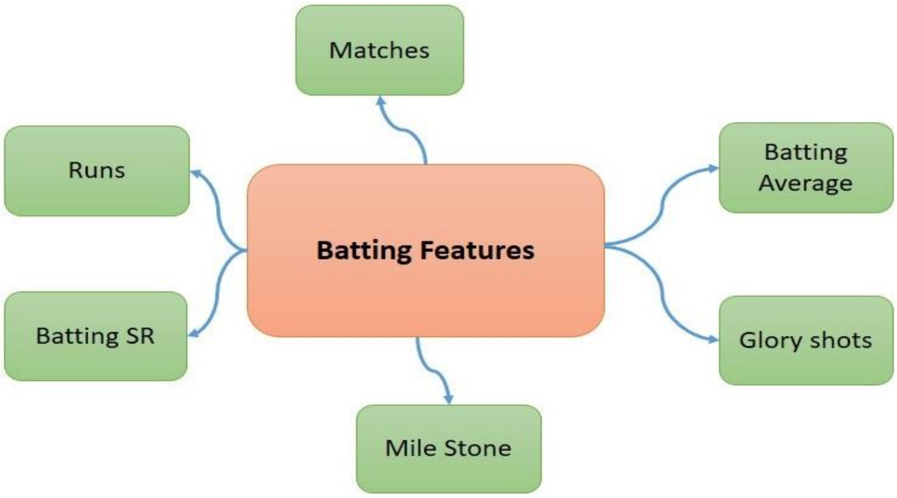

Figure 4: Features selected to measure batting performance

- **Matches:** This feature represents the number of matches played by the batsman in the Series. It reflects the value of the player, and it is a benefit criterion.

- **Runs:** Runs scored by the batsman indicate the effectiveness of the batsman. It is one of the important features that indicate the batting performance of the player. Sometimes it is the sole feature that is used to decide the best batsman. It is also a beneficial feature.

Doi : https://doi.org/10.54216/IJNS.200111
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- **Batting Average**: Batting Average (Bat. Av.) is also a benefit criterion that is used to measure the performance of the batsman. It is extracted using three different features, namely runs scored, inning played, and the number of not outs. It is calculated using the following equation.

$$Bat.Av. = \frac{\#\,Runs\,Scored}{\#\,Innings\,played - \#\,not\,outs} \tag{24}$$

- ***Batting Strike Rate:*** Batting Strike Rate (Bat. SR) represents the ability of a batsman to score runs quickly. Batsman having high strike rates are the first choices of the teams in T-20 cricket. Mathematically, it is calculated using the following equation.

$$Bat.SR = \frac{\#\,Runs\,scored}{\#\,Balls\,played} \tag{25}$$

- ***Mile Stone***: In cricket, the Milestone is referred to as the inning in which the player has scored fifty or more runs. This feature shows the effectiveness of the batsman in the match and in the Series.

- ***Glory Shots:*** A glory shot is defined as a shot in which the batsman sends the ball outside the boundary and earns four or six runs in one ball without running. This feature represents the efficiency of batsmen to score runs quickly.

Table 2: Features included in different papers to evaluate the performance of batsmen.

Reference\Features	Matches	Runs	Bat. Av.	Bat. SR	Mile Stone	Glory Shots
[25]	×	×	✓	✓	✓	✓
[34]	×	×	✓	×	✓	
[28]	×	×	×	✓	×	×
[35]	✓	✓	×	✓	×	×
[30]	×	✓	✓	×	×	×
Proposed Approach	✓	✓	✓	✓	✓	✓

B. Weight Calculation

The objective weights of the features were calculated using two different weight calculation methods discussed in section 2.4. The obtained weights of the features are presented in Table 3.

Table 3: Weights of the Batting Features

Feature	Matches	Runs	Average	Strike Rate	Mile Stone	Glory Shots
CRITIC Weights	0.183943	0.097528	0.253684	0.247414	0.117428	0.100003
Entropy Weights	0.054482	0.142084	0.084302	0.010189	0.536625	0.172319

C. Convert Crisp Values into SVN

After feature selection and calculation of the weights of the selected features, the crisp data was converted to SVNS using the approach discussed in section 3. Table 4 shows a few instances of the selected feature after conversion to SVN.

Table 4: Few instances of the selected features of batsman after conversion to SVN

Player	Matches	Runs	Average	Strike Rate	Mile Stone	Glory Shots
RD Gaikwad	(0.9167, 0.0833, 0.0833)	(1.0000, 0.0000, 0.0000)	(0.5307, 0.4693, 0.4693)	(0.5732, 0.4268, 0.4268)	(0.8333, 0.1667, 0.1667)	(1.0000, 0.0000, 0.0000)
F du Plessis	(0.9167, 0.0833, 0.0833)	(0.9961, 0.0039, 0.0039)	(0.5285, 0.4715, 0.4715)	(0.5992, 0.4007, 0.4007)	(1.0000, 0.0000, 0.0000)	(0.9467, 0.0533, 0.0533)

Doi : https://doi.org/10.54216/IJNS.200111
Received: June 18, 2022 Accepted: December 17, 2022

KL Rahul	(0.6667, 0.3333, 0.3333)	(0.9823, 0.0176, 0.0176)	(0.7978, 0.2022, 0.2022)	(0.6073, 0.5831, 0.5831)	(1.0000, 0.0000, 0.0000)	(0.8800, 0.1200, 0.1200)
S Dhawan	(0.9167, 0.0833, 0.0833)	(0.9061, 0.0939, 0.0939)	(0.4343, 0.5657, 0.5657)	(0.4169, 0.5831, 0.5831)	(0.5000, 0.5000, 0.5000)	(0.8933, 0.1067, 0.1067)
GJ Maxwell	(0.8333, 0.1667, 0.1667)	(0.7613, 0.2387, 0.2387)	(0.4904, 0.5096, 0.5096)	(0.6784, 0.3215, 0.3215)	(1.0000, 0.0000, 0.0000)	(0.7600, 0.2400, 0.2400)

D. Apply Neutrosophic TOPSIS

After converting to SVNS, neutrosophic TOPSIS discussed in section 3 was applied, and RC scores of the players were obtained. The players were sorted in descending order of the RC score, and the batsman having the maximum RC score was recommended as the best batsman. The RC score of the batsman and their ranks with two different weights is presented in Table 5. The best batsman of the Series identified by our proposed approach is RD Gaikwad. He is also the recipient of the best batsman award, which is decided by considering the number of runs scored in the Series as the sole criterion.

Table 5: Batsman Ranking: Rank List of batsmen calculated using Neutrosophic TOPSIS

		Batsman Rank using Neutrosophic TOPSIS with			
		CRITIC Weight		**Entropy Weight**	
S. No.	**Player Name**	**RC**	**Rank**	**RC**	**Rank**
1	RD Gaikwad	0.4915	1	0.4821	1
2	F du Plessis	0.4264	2	0.4044	2
3	KL Rahul	0.4058	3	0.3813	3
4	S Dhawan	0.2015	13	0.2123	12
5	GJ Maxwell	0.3758	4	0.3442	5
6	SV Samson	0.1498	18	0.1567	16
7	PP Shaw	0.2178	12	0.2094	13
8	Shubman Gill	0.3349	7	0.3545	4
9	MA Agarwal	0.1412	21	0.1883	14
10	RR Pant	0.1692	16	0.1482	17
11	D Padikkal	0.1220	26	0.1126	20
12	V Kohli	0.1333	24	0.1424	18
13	RA Tripathi	0.3377	6	0.3362	6
14	N Rana	0.3293	9	0.3352	7
15	RG Sharma	0.1047	30	0.0726	30
16	VR Iyer	0.1111	28	0.1785	15
17	MM Ali	0.1418	20	0.0786	28
18	SA Yadav	0.1365	23	0.0987	21
19	AB de Villiers	0.1619	17	0.0959	23
20	Q de Kock	0.0742	39	0.0869	24
21	MK Pandey	0.1020	19	0.1267	19
22	KS Williamson	0.0865	35	0.0862	25
23	AT Rayudu	0.1869	14	0.0975	22
24	JC Buttler	0.1368	22	0.0548	33
25	YBK Jaiswal	0.1202	27	0.0553	32

Doi : https://doi.org/10.54216/IJNS.200111
Received: June 18, 2022 Accepted: December 17, 2022

26	JM Bairstow	0.1110	29	0.0854	26
27	KA Pollard	0.1458	19	0.0561	31
28	SO Hetmyer	0.3336	8	0.3239	9
29	Ishan Kishan	0.0878	33	0.0825	27
30	S Dube	0.0607	43	0.0453	34
31	RA Jadeja	0.3592	5	0.3253	8
32	KD Karthik	0.3229	10	0.3135	10
33	DA Warner	0.0426	49	0.0784	29
34	CH Gayle	0.0672	41	0.0236	44
35	KS Bharat	0.0728	40	0.0434	37
36	AD Russell	0.1324	25	0.0447	35
37	SS Iyer	0.0506	46	0.0178	47
38	DJ Hooda	0.0856	36	0.0427	39
39	SK Raina	0.0793	38	0.0435	36
40	R Tewatia	0.0896	32	0.0300	42
41	M Shahrukh Khan	0.0866	34	0.0183	46
42	SPD Smith	0.0431	48	0.0115	49
43	E Lewis	0.1761	15	0.0427	38
44	JJ Roy	0.0600	44	0.0406	40
45	AK Markram	0.0566	45	0.0124	48
46	KH Pandya	0.0798	37	0.0240	43
47	EJG Morgan	0.3095	11	0.3093	11
48	WP Saha	0.0294	50	0.0091	50
49	HH Pandya	0.0660	42	0.0193	45
50	DA Miller	0.0452	47	0.0393	41

4.2. Use Case 2: Recommending the Best Bowler

A use case 2 is presented to analyze the bowling performance. Unlike use case 1, the features selected to analyze the bowling performance are both cost and benefit features. The data of IPL_2021 was collected from authentic sources to measure bowling performance. Some instances of the data obtained are presented in Table 6.

Table 6: Few Instances of Data obtained to measure Bowling Performance

Player	Mat	Inns	Overs	Mins	Runs	Wkts	BBI	Ave	Econ	SR	4	5
HV Patel	15	15	56.2	0	459	32	May-27	14.34	8.14	10.5	1	1
Avesh Khan	16	16	61	0	450	24	Mar-13	18.75	7.37	15.2	0	0
JJ Bumrah	14	14	55	0	410	21	Mar-36	19.52	7.45	15.7	0	0
SN Thakur	16	16	59.5	1	527	21	Mar-28	25.09	8.8	17	0	0
Mohammed Shami	14	14	52.4	1	395	19	Mar-21	20.78	7.5	16.6	0	0

A. Feature Selection

There are various features that indicate the bowling performance of the players [36]. Table 6 presents features that indicate bowling performance. Table 7 shows that previous studies intended to measure bowling performance considered only a few features. We selected the maximum number of features, and all the selected features were used in previous studies. The selected features are discussed below.

Doi : https://doi.org/10.54216/IJNS.200111
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Table 7: Features included in different papers to measure the performance of bowlers.

Reference\Features	Matches	Wickets	Bowling Average	Economy	Bowling Strike rate
[25]	×	×	✓	✓	✓
[34]	×	×	✓	×	✓
[30]	×	✓	✓	×	×
Proposed Approach	✓	✓	✓	✓	✓

- ***Matches:*** They represent the number of matches played by the bowler in the Series. It is a beneficial feature. The reason to include this important feature in the study is very simple we are recommending the best player of the Series. So, the recommended player must have played the maximum number of matches.

- ***Wickets:*** It is a beneficial feature that represents the number of wickets taken by the bowler in the Series. It is one of the most important features that represent the bowling performance, and sometimes it is the sole criterion to decide the best bowler of the Series.

- ***Bowling Average:*** It is one of the important features that is used to quantify bowling performance. It is a cost criterion. Mathematically, the bowling average is calculated using the equation.

$$Bowling\ Average = \frac{\#\ Runs\ conceded}{\#\ Wicktes\ taken} \tag{26}$$

- ***Economy:*** Economy is a cost criterion used to measure bowling performance. It represents the average number of runs conceded per over. Mathematically, it can be represented by using the equation.

$$Economy = \frac{\#\ Runs\ conceded}{\#\ Overs\ Bowled} \tag{27}$$

- ***Bowling Strike Rate:*** Unlike the batting strike rate, the bowling strike rate is a cost criterion. It represents the average number of balls bowled by a bowler to take a wicket. The mathematical notation for bowling strike rate is given by the following equation.

$$Bowling\ Strike\ Rate = \frac{\#\ Balls\ Bowled}{\#\ Wicktes\ taken} \tag{28}$$

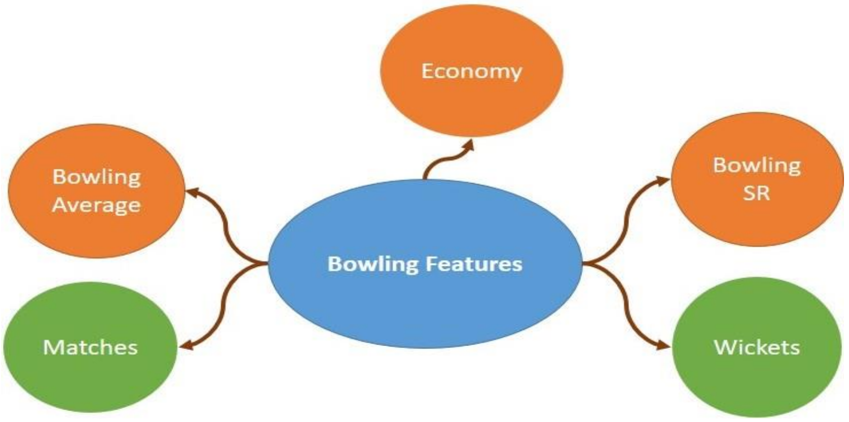

Figure 5: Features selected to measure the bowling performance

B. Weight Calculation

Objective weights of the bowling features were calculated using the methods discussed in section 2.4. The weights of the bowling features are given in table 8.

Doi : https://doi.org/10.54216/IJNS.200111
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Table 8: Weights of Bowling Features

Feature	Matches	Wickets	Bowling Average	Economy	Bowling Strike Rate
CRITIC Weights	0.208802	0.188416	0.172629	0.228175	0.201979
Entropy Weights	0.214896	0.353017	0.212272	0.029016	0.190799

C. **Convert Crisp Values into SVN**

After feature selection, the crisp data of the selected features were converted into SVNS using the technique discussed in section 3. Table 9 shows a few instances of the bowling features after conversion to SVN.

Table 9: Few instances of the selected features of bowlers after conversion to SVN

Player	Matches	Wickets	Bowling Average	Economy	Bowling Strike Rate
HV Patel	(0.8571, 0.1428, 0.1428)	(1.0000, 0.0000, 0.0000)	(0.0281, 0.9719, 0.9719)	(0.4805, 0.5195, 0.5195)	(0.0063, 0.9937, 0.9937)
Avesh Khan	(0.9286, 0.0714, 0.0714)	(0.7037, 0.2963, 0.2963)	(0.1314, 0.8686, 0.8686)	(0.3043, 0.6957, 0.6957)	(0.1546, 0.8454, 0.8454)
JJ Bumrah	(0.7857, 0.2143, 0.2143)	(0.5926, 0.4074, 0.4074)	(0.1494, 0.8506, 0.8506)	(0.3227, 0.6773, 0.6773)	(0.1703, 0.8297, 0.8297)
SN Thakur	(0.9286, 0.0714, 0.0714)	(0.5926, 0.4074, 0.4074)	(0.2799, 0.7201, 0.7201)	(0.6316, 0.3684, 0.3684)	(0.2114, 0.7886, 0.7886)
Mohammed Shami	(0.7857, 0.2143, 0.2143)	(0.5185, 0.4815, 0.4815)	(0.1790, 0.8210, 0.8210)	(0.3341, 0.6659, 0.6659)	(0.1987, 0.8013, 0.8013)

D. Apply Neutrosophic TOPSIS

After the conversion of crisp data to SVNS, the neutrosophic decision matrix and weighted neutrosophic decision matrix was formed. After that, the neutrosophic positive ideal and neutrosophic negative ideal solutions were identified. The distance between the positive ideal and negative ideal solutions was calculated. After that, equation (22) was used to calculate the RC score. In the final step, the list of players was sorted in descending order of RC score to identify and recommend the best bowler of the Series. The rank list of bowlers calculated by our proposed approach is presented in Table 10. The proposed approach identifies HV Patel as the best bowler when the RC score is calculated using two different objective weights. He is also the recipient of the best bowler award, which was decided on the basis of the number of wickets only.

Table 10: Bowler Ranking: Rank List of bowlers calculated using Neutrosophic TOPSIS

		Bowler's Rank using Neutrosophic TOPSIS			
		CRITIC Weight		Entropy Weight	
S. No	**Player Name**	**RC**	**Rank**	**RC**	**Rank**
1	HV Patel	0.7423	1	0.7538	1
2	Avesh Khan	0.6355	3	0.6731	3
3	JJ Bumrah	0.6000	7	0.6283	5
4	SN Thakur	0.6086	4	0.6509	4

Doi : https://doi.org/10.54216/IJNS.200111
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5	Mohammed Shami	0.5939	9	0.6190	7
6	Arshdeep Singh	0.5757	15	0.6030	12
7	YS Chahal	0.6032	5	0.6253	6
8	Rashid Khan	0.5952	8	0.6146	9
9	CV Varun	0.6826	2	0.7071	2
10	JO Holder	0.5635	25	0.5829	20
11	SP Narine	0.5900	10	0.6052	10
12	AR Patel	0.5779	13	0.5916	14
13	CH Morris	0.5501	29	0.5825	21
14	K Rabada	0.5802	11	0.6043	11
15	DJ Bravo	0.5678	21	0.5862	18
16	C Sakariya	0.5692	19	0.5916	15
17	Mustafizur Rahman	0.5664	22	0.5907	16
18	DL Chahar	0.5744	17	0.5988	13
19	LH Ferguson	0.5595	27	0.5737	27
20	RD Chahar	0.5629	26	0.5774	24
21	RA Jadeja	0.6005	6	0.6158	8
22	TA Boult	0.5683	20	0.5871	17
23	A Nortje	0.5651	23	0.5723	28
24	Ravi Bishnoi	0.5638	24	0.5720	29
25	M Prasidh Krishna	0.5381	36	0.5660	31
26	AD Russell	0.5337	37	0.5738	26
27	Shivam Mavi	0.5573	28	0.5684	30
28	JR Hazlewood	0.5444	31	0.5630	32
29	Mohammed Siraj	0.5759	14	0.5861	19
30	PJ Cummins	0.5324	38	0.5531	35
31	KA Jamieson	0.5221	41	0.5544	34
32	SM Curran	0.5036	43	0.5445	40
33	R Tewatia	0.5297	39	0.5559	33
34	Shahbaz Ahmed	0.5702	18	0.5748	25
35	NM Coulter-Nile	0.5490	30	0.5518	36
36	S Kaul	0.5257	40	0.5392	41
37	R Ashwin	0.5098	42	0.5175	43
38	A Mishra	0.5395	34	0.5487	38
39	MM Ali	0.5783	12	0.5811	23
40	B Kumar	0.3163	47	0.3424	47
41	JDS Neesham	0.5436	32	0.5494	37
42	CR Woakes	0.5402	33	0.5467	39
43	KA Pollard	0.5756	16	0.5815	22
44	L Ngidi	0.4390	46	0.4377	46
45	Harpreet Brar	0.5392	35	0.5387	42
46	KK Ahmed	0.5026	44	0.5135	44
47	KH Pandya	0.4732	45	0.4838	45

Doi : https://doi.org/10.54216/IJNS.200111
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5. Discussion

The main objective of this paper was to propose an effective solution for performance analyses and recommendations of the best players in a series. In this direction, we proposed an approach that collects data from the web, selects important features, calculates the objective weights of the features, and converts the crisp data to SNVS. In the final step, apply TOPSIS on the SVNS data to identify the best players. The results obtained by using different weights with Neutrosophic TOPSIS were compared and evaluated using the Kendall Tau correlation coefficient. The advantages of the proposed work can be summarized as follows:

A. Feature Selection

One of the important aspects of our proposed work is that we have selected a sufficient number of features for evaluating the performance of the players. In the case of the batsman, we have selected six different features to measure the performance. Table 2 shows that a maximum of three features have been used by other studies to evaluate batting performance. Similarly, Table 7 shows that we have used five features to measure the performance of the bowlers. In contrast, a maximum of three features have been used in past studies for measuring bowling performance. We have selected only those features that were used by other experts to measure the performance. The selected features show different attributes of the players like experience, temperament, ability to score runs quickly, ability to take wickets, consistency, etc. So, our set of selected features covers different aspects of the player's performance and also avoids the curse of dimensionality.

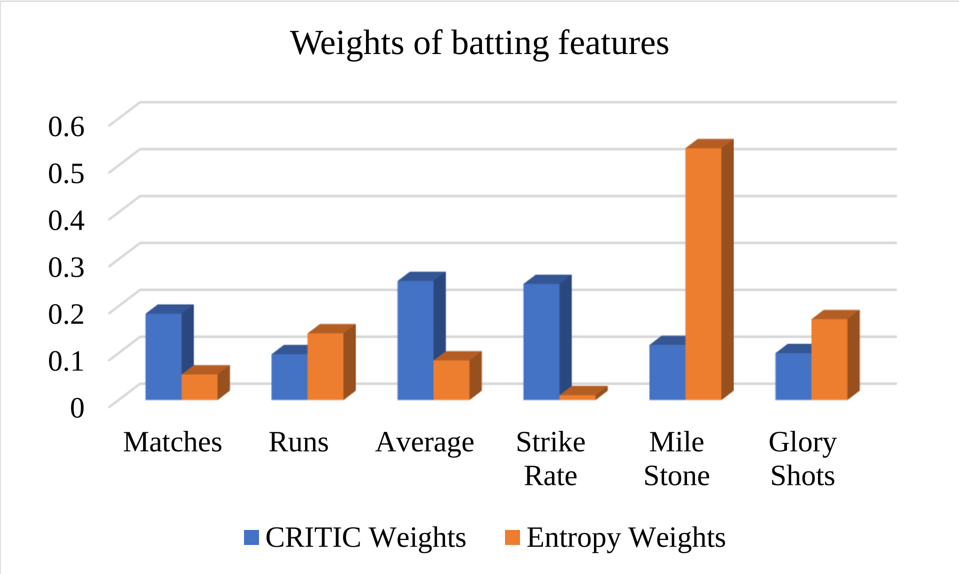

Figure 6: Comparison of weights of batting features

B. Comparative Analysis

Table 11 shows the best players found using different weights with Neutrosophic TOPSIS. Figure 6 shows the comparison of weights of batting features. It shows that the CRITIC method gives maximum weight to batting average, whereas entropy methods give maximum weight to Milestone. Also, the variance in the weights obtained by the entropy method is more as compared to the variance of weights obtained by the CRITIC method. It can be observed that all these differences and variations in weights do not change the best alternative. The best batsman identified by our proposed approach is RD Gaikwad. He was also the recipient of the best batsman award, decided by the number of runs scored.

Table 11: Best Players found using different weights with Neutrosophic TOPSIS.

Player Type	Objective Weight	Player Name
Best Batsman	CRITIC	RD Gaikwad
	Entropy	RD Gaikwad

Doi : https://doi.org/10.54216/IJNS.200111
Received: June 18, 2022 Accepted: December 17, 2022

Best Bowler	CRITIC	HV Patel
	Entropy	HV Patel

Similarly, Figure 7 shows the comparison of different weights obtained for bowling features. It shows that the Entropy method gives maximum weight to wickets whereas the CRITIC method gives the highest weight to the Economy feature and the variance in the CRITIC weights is less as compared to the Entropy weights. Despite all these differences and variations in weights obtained by two different methods, HV Patel is identified as the best bowler with both weights. He was also the recipient of the best bowler award, which was decided on the basis of the number of wickets.

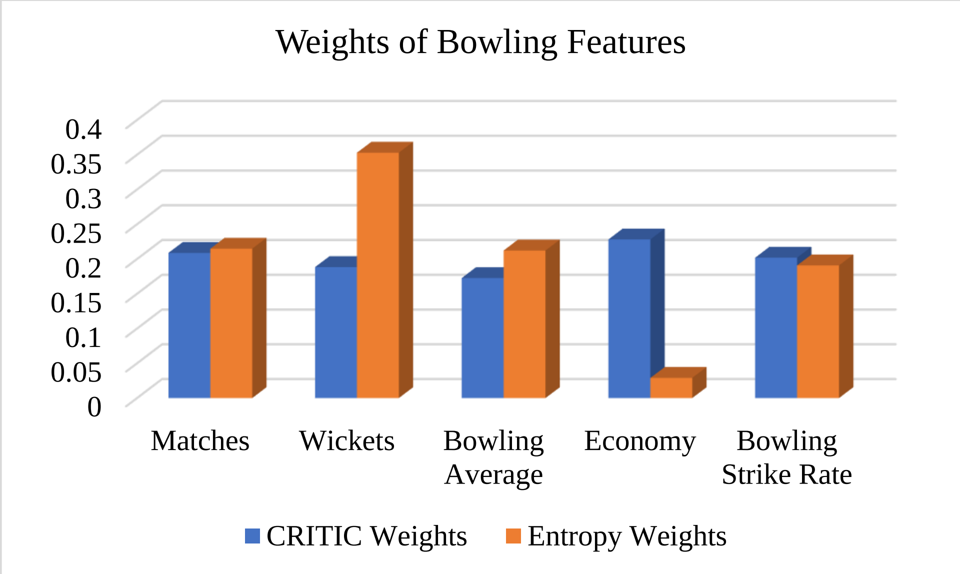

Figure 7: Comparison of weights of bowling features

We compared and evaluated the degree of concordance between the ranked lists using the Kendall tau (τ) rank correlation coefficient presented by equation (10). The value of τ for batsmen ranks lists is 0.72 and for bowler's ranks lists is 0.83. As the value of τ is very close to 1, it shows strong associations between the ranked lists and the consistency of the proposed approach. We have also evaluated our ranked lists using the set intersection method, which computes the overlapping score between two ranked lists [37]. The significance of the set intersection method is that it calculates the percentage of the overlapping elements in the two ranked lists, and the overlapping score changes with the change in the rank order at different positions [38]. Figure 8 represents the set intersection score for different depths of ranked lists. It can be observed from figure 8 that overlapping score for the top 5, top 10, and top 15 is 80%, 87%, and 100%, respectively, for both batting and bowling rank lists. The overlapping score is 80% for batting lists and 90% for bowling lists for the top 20. The high value of overlapping scores for two ranked lists and at different depths of the lists shows that the rank lists generated by using different weights are similar.

Doi : https://doi.org/10.54216/IJNS.200111
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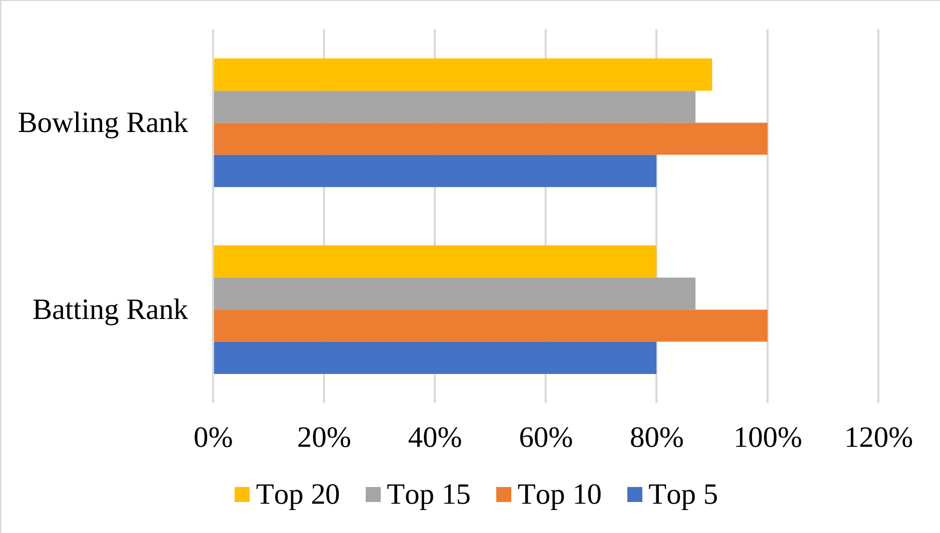

Figure 8: Set Intersection score for different depths of ranked lists

Since the best players identified with two different objective weight methods are the same, this depicts that our proposed approach is consistent and effective in finding out the best player. This proves that the proposed approach can be extended to find out the best resources in other real-life situations. It is also observed from the two case studies that variations in the weights obtained by the CRITIC method are low as compared to the variation in weights obtained by the Entropy method. Therefore, we recommend the use of the CRITIC method while applying neutrosophic TOPSIS to identify the best alternative in any domain of life.

6. Limitations and Future Direction

In this section, we discuss some limitations of the study and also suggest some future directions where the proposed approach can be applied. We believe that researchers working in the related domain will find these suggestions useful.

6.1. Incorporation of other Contextual Criteria Information

In this work, we considered only numeric performance indicators to measure the performance and recommend the best player. There are other non-numeric conditions like the strength of the opposition, playing conditions, and match situations, which also affect the performance. So, the incorporation of these non-numeric performance indicators may further improve the process of performance analysis and recommendation of the best players.

6.2. Recommend the Best Fielder and All-rounder of the Series

In this work, we proposed an approach to identify and recommend the best batsman and the best bowler of the Series. This approach can be extended further to identify and recommend the best fielder and best all-rounder of the Series by selecting appropriate performance indication features.

6.3. Recommend the Players for Specific Positions and Opposition

A deep analysis of players' performance at different positions may help in identifying the best player for each position. A similar approach may be designed to recommend the best player for specific opposition.

6.4. Application to Other Sports

This paper recommends the best batsman and the best bowler of the Series in cricket. The proposed approach may be used to identify and recommend the best players in other sports like hockey, football, tennis, etc.

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7. Conclusion

In this paper, we proposed a Neutrosophic MCDM approach to automate the process of performance evaluation and recommendation of the best players in a sports league. A systematic approach for data collection, feature selection, weight calculation, conversion of crisp data to neutrosophic data, and Application of TOPSIS for performance evaluation and recommendation of best players is presented. A case study on the data of IPL 2021 is presented to demonstrate the applicability of the proposed approach. The proposed approach collected the data of players who played IPS 2021 from authentic web sources and selected important features from the data in order to overcome the problem of the curse of dimensionality. Then the crisp data was converted to SNVS to handle vagueness, indeterminacy, and inconsistency in information. The weights of the criteria were calculated using two well-known and extensively used objective weight calculation methods. In the final step, neutrosophic TOPSIS was applied, and ranked lists of batsmen and bowlers were computed. The ranked lists were evaluated and compared using Kendal Tau (τ) coefficient. It is observed from the results that the best alternative obtained from the two different ranked lists is the same, and the values of τ are 0.83 for the bowlers ranked lists, and 0.72 for the batsmen ranked list. All these results prove the consistency and effectiveness of the proposed approach. Some limitations and future work have been discussed. The main contributions of the proposed approach are (i) It fills the gap in the sports science literature regarding the performance evaluation and recommendation of the best players of the Series. (ii) It proposed an efficient and effective approach to combat vagueness, uncertainty, inconsistency, and indeterminacy in real-life decision-making problems, (iii) it compares the performance of two different objective weight calculation methods and recommends the best among the two. We believe that the proposed approach will be useful for performance evaluation and recommendation of best resources in other domains of real.

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