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An Integrated Approach to Select the Dream Team for a Cricket Match

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Abstract:
Due to the broadcast of cricket matches globally, a Cricket team's performance has become a hotly debated topic. Capitalizing on this, various sports fantasy apps based on formulating the best team have emerged. The best team is selected based on certain criteria such as number of batsmen, bowlers, all-rounders, wicket-keepers and pliers from each team. Another constraint in selecting the players of the dream team is the total points available. In this regard, an integrated approach is developed in this paper. The proposed approach integrates cross-entropy method and weighted sum method (WSM) with goal programming problem (GPP). The proposed algorithm extracts the performance of the players by web scraping. The cross-entropy and WSM computes the points for each player based on their performance giving high weightage to the recent games. The advantage of the proposed algorithm is that it readjust the weights of the factors based on the performance of the players in the recent games. Then the selection of the players is done by the GPP part of the proposed approach where the decision variable is binary which implies its value is 1 if a particular player is selected in the team else it is 0. In order to test the practicality of the proposed approach, it is applied for selecting the dream team for a cricket match between India and New Zealand.

Keywords: Cricket, Dream team selection, Web scraping, Weighted average method, Goal Programming Problem, Cross-entropy method

1. Introduction

Cricket has shown exponential growth in this decade with the increase in the number of tournaments like world cups, bilateral series and the most important being IPL .This has led to the birth of fantasy sports apps like Dream11, MPL etc. with approximately 13 crores users who face the challenge of building a team subject to a budget constraint. The user is required to select players from both the teams participating ,with each player having a certain cost- calculated based on his ability. A minimum number of players must be selected from each team and the constraints in terms of the number of batsmen, wicket-keepers,all rounders,and bowlers must be followed. Each player is given a score at the end of the match based on his performance. The user with the highest scores wins rewards.

However, with the plethora of talent and vast pool of players ,player selection-the best playing 11 becomes significantly challenging. A lot of factors like the player's career statistics, player category like for example, batsmen are sorted on the criteria of batting average, strike rate, centuries and so on, while bowlers are sorted on the basis of bowling average, economy rate etc. The players' recent form is also given substantial weightage during the selection process. Moreover the team is fixed throughout the match and there is no room for substitution like in case of football.

We thus target to reduce the effort and time spent by the various players by providing an optimal solution. We have assumed that every player is fit and there is no injury scare and there is ground neutrality. The dataset contains cumulative performances of players across all formats and gives experience considerable importance. Players were divided into four categories of batsman, bowlers, all-rounders and wicket-keepers. As far as conditions are concerned, to be selected as an all-rounder a player must have scored at least 400 runs and taken a bare minimum of 25 wickets. The problem statement therefore has a binary decision variable and can be treated as a classic Knapsack problem. We have used a Linear Programming model and for the ranking method, some of the the weights given for various skills like strike rate,runs have been extracted from Dream11 and then normalized and rounded off .

The paper has the following format: - Section 1 provides a brief overview of the study undertaken, followed by the problem statement under considerations and the tools used. Section 2 gives the literature review pertaining to the work done in this field. Section 3 defines the material and methods. Section 4 analyzes the proposed solution with respect to India-New Zealand and Section 5 discusses some of the limitations of this study and further course of work.

2. Review of the contemporary literatures

Singla and Shukla (2020) in their paper [1] used Integer Programming, by using Gurobi library in Python. and analyzed the problem through Markowitz Optimization, by penalizing inconsistency .The element of prediction was removed and basis of player selection was on the mean score and standard deviation of previous matches. Decision variable was a $(30x3)$ matrix and was binary. Agarwal and Yadav (2017) in their paper [2] considered Player Performances with different Teams, giving importance to Last 5 Performances. Analysis was performed using Hive and Hadoop .The proposed approach was up to 91% accurate. Main factors affecting the player's performance were averages and venue. The data were extracted from sports.ndtv.com, which were further converted into 1000's of tuples. The stats were taken till Jan, 2017 and the predictions were tested in the matches after that. Patil et. al., (2020), believed that predicting players' performance is not enough. Rather, depending on the historical stats a decision has to be passed whether the player qualifies as an ideal player to be considered. The possibility of biased selections is minimized. The system initially analyses the available positions in the team, once a bunch of players are selected. The decision trees are to be designed in such a way as to provide a balanced team. Interestingly they have taken three star players as input who form the base for further prediction. Random Forest had optimum precision and was the most accurate classifier [3]. Li et. al., (2021) in their paper [4] conducted a multivariate logistic regression analysis to examine the relationship between the winning probability and game outcomes. To ensure that the winning probability is within [0,1], an S-shape logistic regression method was adopted. By planning the playing time among players in the court, they address a DEA-based player portfolio efficiency analysis to optimally choose players. The players' data would help to predict the future by training the model and reduce average inefficiency status. Based on a four-season dataset from the 2011–12 season to the 2014–15 season, they obtained the prediction results for the 2015–16 regular season. It shows that the DEA-based data-driven approach was accurate. They assume that the past performance is a good reference of future performance. Through the application to Golden State Warriors in the NBA, they found their approach to be fruitful. Sarda and Iyer (2008), in their paper [5], employed neural networks to predict each cricketer's future performance. They classify cricketers into three categories – performer, moderate and failure and collected data on cumulative player performance from 1985 onwards until the 2006–2007 season. Based on the ratings generated and by applying heuristic rules they recommend cricketers to be included in the World Cup 2007. Their results show that the neural networks can indeed provide valuable decision support in a team selection process. Based on the opinions of cricket experts ,they chose eight countries from the ten full members of the ICC. Neural networks were created using a commercial software product Statistica 7.1 by Statsoft, Inc but only the best networks were retained by the Intelligent Miner mode. Barot et. al., (2020) in their paper [6] recognized few crucial factors like team form and team strength in predicting the match outcome apart from the conventional features like the toss, venue of the games etc. Further, based on Batting Index and Bowling Index, a novel analysis of Batting and Bowling was proposed. Machine Learning algorithms like SVM, Logistic Regression, Random Tree, Random Forest and Naive Bayes were applied. The most accurate results were plotted. Decision Tree and Logistic Regression algorithms gave an accuracy of 87% and 95% respectively. The dataset used was collected from ‘kaggle’ Two datasets were used. The first gave ball-to-ball information while the second had the summary of each match, including the winner, the winner of the toss. The lowest accuracy obtained starts from 81.6% for Naive Bayes classifier. Goel et. al., (2021) in their paper [7] proposed methodology that not only incorporates the dynamically updating game context as the game progresses, but also includes the relative strength between the two teams playing the match. They make predictions on the outcome of a match when the second team starts batting. Metrics was tracked as a function of each ball of each over throughout the match during the second innings. Initially, they tried Support Vector Machine, Random Forest, Boosting, Bagging, and Gradient Boosting with an accuracy of 76.47%(+/–3.77%). With deep learning, they tried the various flavors of LSTM and GRU like vanilla, Bidirectional and stacked to train their models and the results found were accurate up to 76.13%. They were tested using approaches such as one-to-one sequencing, one-to-many sequencing, many-to-one sequencing. Player data for IPL was scraped from the archive section of cricket fan site cricinfo.com4 for the seasons 2008 to 2019 and combined into two datasets for matches and deliveries. From these datasets, feature sets were constructed using automated excel macros. They had a total of 90 features, which when fed to the model gave poor results due to the “Curse of Dimensionality”. Sankaranarayanan et. al., (2014) in their paper [8] build a prediction system that takes the instantaneous state of a match, and predicts future match events resulting in a victory or loss. They model the game using nearest-neighbor clustering algorithms and linear regression. They rely on modern rules like free hits and use of two new balls and power plays They developed separate models for home runs and away runs. Ridge Regression and attribute bagging algorithms were used on the features to incrementally predict the runs scored in the innings. They demonstrated the quality and accuracy of their predictions with a set of experiments on ODI cricket data. Ahmed et. al., (2017) in their paper [9] introduced the idea of Co-players, Team and opposite teams for Rising Star Prediction. Co-player has played matches during some common time span relatively or could be one who belongs to the same or opponent team and A rising cricketer currently did not hold attractive records, but has the potential to be a star performer in future based on improved stats. Thus they concluded that RS’s were the significant contributors to their teams.9 and 11 features were defined for the prediction of batting and bowling rising stars, respectively. Based on weighted average and performance evaluation metrics, two types of datasets were generated. While employing generative (BN and NB) and discriminative (SVM and CART) machine learning algorithms,the defined features were tested. The remaining models were outperformed by NB. Rankings were finally compared with the ICC rankings during the 2013–16 season. Groll et. al., (2018) in their paper [10] used three different approaches for the scores of football matches: Poisson regression models, random forests and ranking methods.Ranking methods and the random forests proved better. Data was based on all matches from the four previous FIFA World Cups 2002 – 2014.They believed they could improve the predictive power by combining the random forest with the team ability parameters .Winning probabilities were obtained by simulating the FIFA World Cup 2018 repeatedly.

Diverse Factors were considered with the 23-player-squad selected.The average age of each squad was collected and the number of players in the semifinals of the UEFA Champions League (CL) and UEFA Europa League (EL) were counted as a measurement of the success of the players on club level. The maximum and second maximum number of teammates playing together in the same club were also counted. Given the expected number of goals, a real result was drawn by assuming two (conditionally) independent Poisson distributions for both scores.

3. The problem under consideration

The game of cricket is played between two teams and each team comprises 11 playing and 4 extra players [18]. The names of all the 15 players for each team are to be announced on or before the toss. Once the name of the players are announced, all the players along with the points (S_j as computed in section 3.2.1 and 3.2.2) from both the teams are segregated and stored in one csv file which is named as the master file. The aim of the study is to select a dream team comprising of the best 11 players from both the sides by abiding the following rules:

a. In order to select the dream team, a total of 100 can be utilized.

b. The minimum and maximum number of batsmen is 3 and 6 respectively.
c. The minimum and maximum number of bowlers is 3 and 6 respectively.
d. The minimum and maximum number of all-rounders is 1 and 4 respectively.
e. There must be one wicket keeper.
f. At most 7 players can be selected from either of the team.
g. In the dream team there is no concept of extra players.

3.1. The problem formulation

The problem under consideration is expressed as a GPP as such:

a) Decision variables

The decision variable of the GPP is y_j which is defined as follows:

$$y_j = 1, \text{ if the } j^{th} \text{ player of the master file is selected}$$
$$y_j = 0, \text{ if the } j^{th} \text{player of the master file is not selected}$$

b) Objective function

The objective function of the GPP is defined as follows:

$$Z = 100 \leq \sum(y_j * Pl_j * S_j) \quad (1)$$

Eq. (1) implies, the sum of the points for the players selected in the dream team must be less than equal to 100. Pl_j is the players in the dream team and S_j is the points for each player.

c) Constraints

The constraints of the GPP as defined by the physical nature of the problem are as follows:

$$\sum(y_j) = 11 \quad (2)$$
$$\sum(y_j * Pl_j) = 11 \quad (3)$$

Eq. (2) and (3) implies that the number of players in the dream team must be 11.

$$\sum(y_j * Pl_j) = \sum(y_j * Ba_{ij}) + \sum(y_j * B_{ij}) + \sum(y_j * Al_{kj}) + \sum(y_j * W_{lj}); \; i \in [4,6], k \in [2,4], l = 1 \quad (4)$$

Eq. (4) implies that the sum of Batsmen, Bowler, All-rounders and wicket keepers is equal to the total number of players in the dream team. In Eq. (4), Ba stands for batsmen, B stands for bowler, Al stands for all-rounder and W stands for wicket-keeper.

$$3 \leq \sum(y_j * Ba_{ij}) \leq 6 \quad (5)$$
$$3 \leq \sum(y_j * B_{ij}) \leq 6 \quad (6)$$
$$1 \leq \sum(y_j * Al_{kj}) \leq 4 \quad (7)$$
$$\sum(y_j * W_{lj}) = 1 \quad (8)$$

Eq. (5), (6), and (7) implies that the minimum and maximum number of batsmen, bowler and all-rounder should be in between 4 to 6, 4 to 6 and 2 to 4 respectively. Eq. (8) implies that there should be one wicket keeper in the dream team.

$$\sum(y_j * Pl_j) = \sum(y_j * Pl_{pj}) + \sum(y_j * Pl_{qj}) \quad (9)$$

Eq. (9) implies that the sum of players from the p^{th} and q^{th} team must be equal to the number of players in the dream team.

$$\sum(y_j * Pl_{pj}) \leq 7 \tag{10}$$

$$\sum(y_j * Pl_{qj}) \leq 7 \tag{11}$$

Eq. (10) and (11) restrict the number of players from each team to exceed 7.

4. Material and Methods

In this section of the paper, a brief description of the dataset scrapped from the internet and the methodology employed for creating the fantasy team is discussed.

4.1. Data collection

In this section of the paper the process of data collection is explained in brief. Data collection is done by the process of web scraping.

4.1.1 Web scraping

In this study, the data is collected from the website "www.espncricinfo.com" by the process of web scraping. Web scraping is the automatic process of extracting a large dataset from different websites [11]. Most web data are unstructured where the web scraping converts the data into structured form which can be utilized for various applications. Some of the common ways of performing web scraping involves using API's and creating the code to scratch the websites [12].

In the present paper, the data are collected for all the players that have played either one of the the three formats of cricket namely twenty-twenty (T20), one day international (ODI) and test match (TM) in the last five years. The scraped data is saved in excel sheet in the csv (comma separated value) format. Different csv files are created for the different formats of cricket. However if a player has retired in the last five years from a particular format then his name is dropped off from the csv file of that particular format. As an example Ben Stokes has played in all the three formats of cricket in the last 5 years but in the month of July 2022 he retired from the ODI format of the game. Hence his name is dropped off the ODI file whereas he is present in the T20 and TM files.

4.1.2. Data segregation

In this step the players data are segregated into different csv files based on their main role in the team. In cricket the players are divided as batsmen, bowlers, all-rounders and wicket-keepers. The rules for segregating the players are as follows:

a) The players who have done atleast one stumpings are grouped as wicket-keepers.
b) The players whose batting as well as bowling averages are at par with each other are grouped as all-rounders.
c) The players with better batting average are grouped as batsmen.
d) The players with better bowling averages are grouped as bowlers.

The flowchart for data collection and data segregation is shown in figure 1

4.2. Preliminaries

In this section of the paper the preliminary concept required for achieving the aims and objectives of the research is described in brief.

4.2.1. Weighted sum method

Weighted Sum Method (WSM) computes the sum of the data by taking into account the degree of importance of each factor of the dataset [13]. The advantage of using WSM is its easy to understand and interpret the result and also easy calculation [14]. In the present study, the points for each player is computed using the WSM. Mathematically,

$$\delta_j = \sum_{i=1}^{n} (w_i . x_{ij})$$

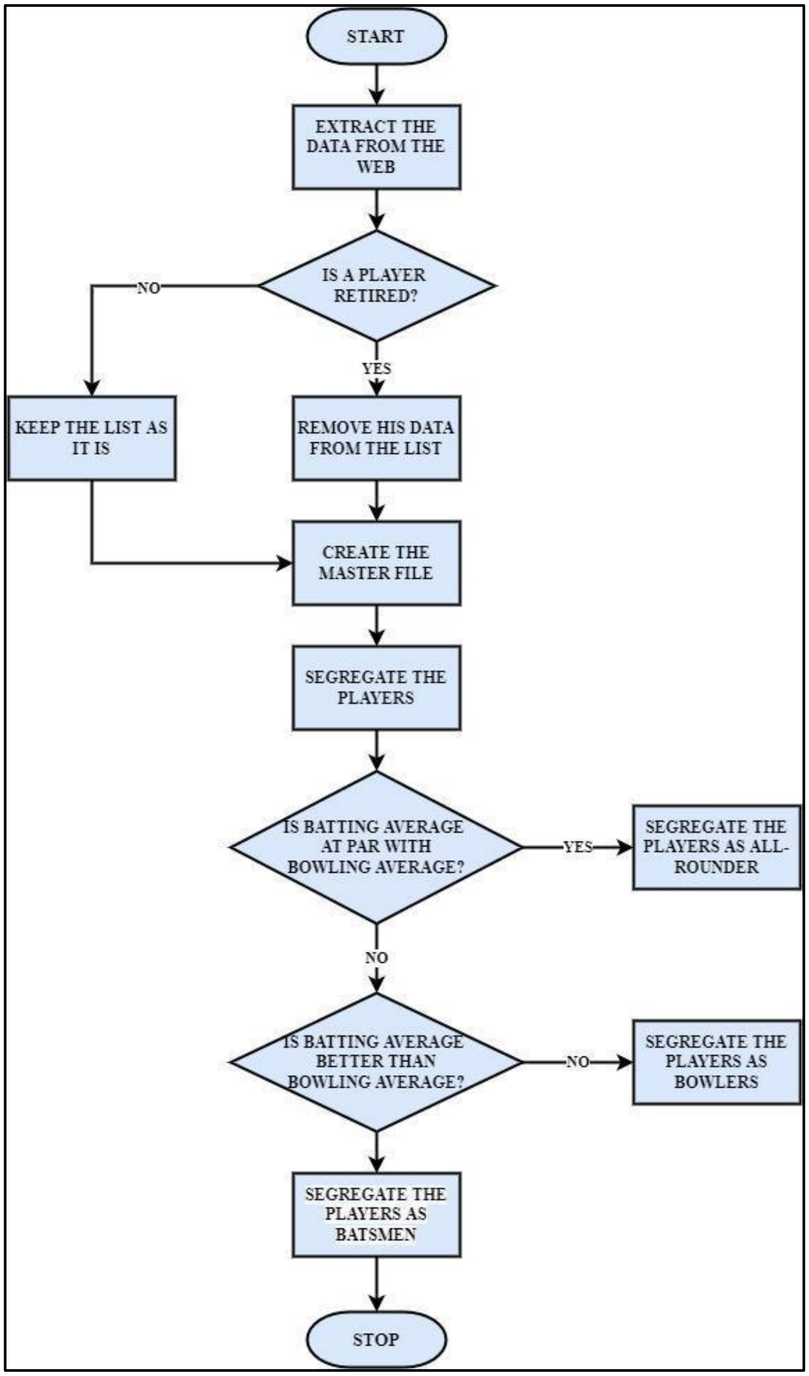

Figure 1: Flowchart for data collection and data segregation.

(12)

Where δ_j is the weighted sum of the entry of the factors as computed for the j^{th} player, w_i is the weightage of the i^{th} factors of the dataset and x_{ij} is the data for the i^{th} factor of the j^{th} player. The weights of the factors are determined using the cross-entropy method which is described in section 4.2.2.

The δ_j computed by the Eq. (12) is further standardized according to the Eq. (13) which is as follows:

$$\Delta_j = \frac{s_j - min(s_j)}{max(s_j) - min(s_j)} \tag{13}$$

The point for j^{th} player (s_j) depends on the Δ_j value as such:
If $\Delta_j \in [0, 0.2]$ then $s_j = 6$, if $\Delta_j \in (0.2, 0.4]$ then $s_j = 7$, if $\Delta_j \in (0.4, 0.6]$ then $s_j = 8$, if $\Delta_j \in (0.6, 0.8]$ then $s_j = 9$ and if $\Delta_j \in (0.8, 1.0]$ then $s_j = 10$

4.2.2. Cross-entropy method

The weightage of the factors implies the degree of importance of each of the factors in making the final decision [15]. In this paper, the weightage of the criteria is computed using the cross-entropy method. The steps of cross-entropy method are as follows [16]:

Step 1: Computing the feature weight (P_{ij}) of the data for the i^{th} factor of the j^{th} player.

$$P_{ij} = \frac{x_{ij}}{\sum_{j=1}^{n} (x_{ij})^2};\ i \in [1, m] \tag{14}$$

Where m is the total number of factors and n is the total number of players

Step 2: Computing the output entropy (e_i) for the i^{th} factor

$$e_i = -k \sum_{j=1}^{n} [P_{ij} * ln(P_{ij})] \tag{15}$$

$$k = \frac{1}{ln(n)} \tag{16}$$

Step 3: Computing the variation factor (g_i) for the i^{th} factor

$$g_i = |1 - e_i| \tag{17}$$

Step 4: Computing the weight (w_i) for the i^{th} factor

$$w_i = \frac{g_i}{\sum_{i=1}^{m} g_i} \tag{18}$$

4.2.3. Goal programming method

Goal programming problem (GPP) is the extension of linear programming problem (LPP) [17]. The objective of the GPP is to achieve a goal by abiding by the constraints set by the physical conditions of the problem under consideration.

4.3. Proposed methodology

The proposed methodology is an integration of the methods as discussed in sections 3.2.1, 3.2.2 and 3.2.3. The flowchart of the proposed methodology is shown in figure 2.

5. Results and Discussion

In this section of the paper, the result obtained after implementing the proposed methodology in solving the problem under consideration is described in brief. Since the cross-entropy method for weight computation of the factors depends on the data, therefore, the weights of the factors vary for each game. In order to show the result a cricket match between India and New Zealand as well as West Indies and Australia is considered.

5.1. Results

The first step of building the dream team is extracting the data by the process of web scraping from www.espncricinfo.com and creating the master file. The second step is computing the weightage of the factor by cross-entropy factor. The weights of the different factors for the batsmen, bowler and all-rounder are shown in table 1.

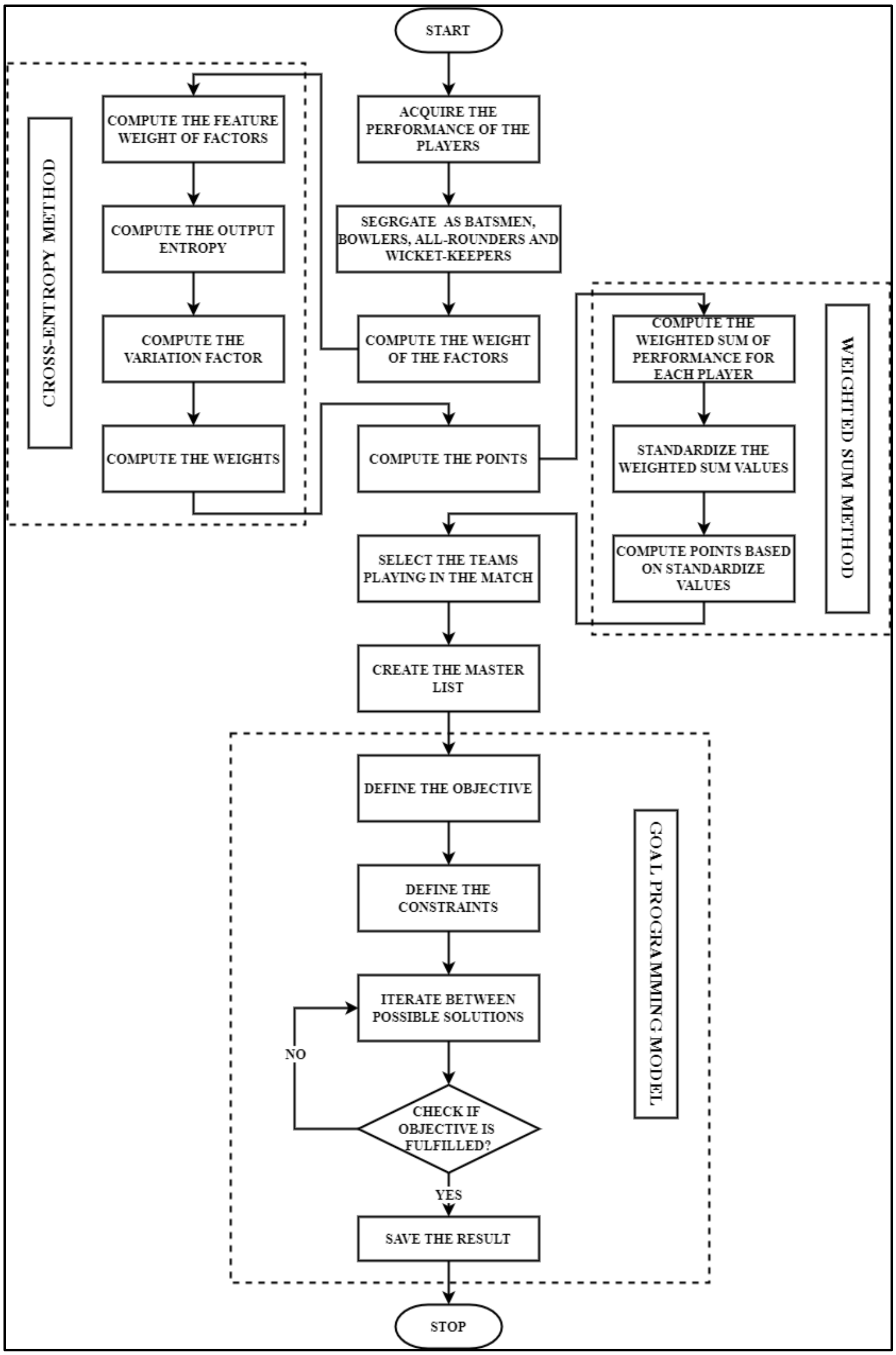

Figure 2: The proposed methodology

Table 1: Weight table

All-rounder							
Game	Batting average	Bowling average	Runs scored	Number of centuries	Number of half-centuries	Best bowling per innings	Wickets taken
Ind vs NZ	0.265	0.243	0.138	0.049	0.050	0.134	0.121
WI vs Aus	0.21	0.275	0.23	0.038	0.039	0.164	0.04

Batsmen				
Game	Batting average	Runs scored	Number of centuries	Number of half-centuries
Ind vs NZ	0.467	0.291	0.066	0.175
WI vs Aus	0.228	0.231	0.255	0.286

Bowling			
Game	Bowling average	Best bowling per innings	Wickets taken
Ind vs NZ	0.317	0.353	0.330
WI vs Aus	0.266	0.254	0.48

The third step of the proposed approach is to compute the points of the players as per the WSM method shown in section 4.2.1. The final step is selecting the best players for the dream team abiding by the rules and regulations as indicated in section 3. The selection is done by GPP. The players selected for the dream team for Ind vs NZ and WI vs Aus are shown in table 2 and 3 respectively.

Table 2: Players in the dream team for Ind vs NZ

Sl. no.	**Player name**	**Position**	**Team**
1	Jasprit Bumrah	Bowler	India

2	Tim Southee	Bowler	New Zealand
3	Trent Boult	Bowler	New Zealand
4	Tom Latham	Wicket-keeper	New Zealand
5	Daryl Mitchell	All-rounder	New Zealand
6	Rohit Sharma	Batsmen	India
7	Shresh Iyer	Batsmen	India
8	Martin Guptill	Batsmen	New Zealand
9	Suryakumar Yadav	Batsmen	India
10	Hardik Pandya	All-rounder	India
11	Michael Bracewell	All-rounder	New Zealand

Table 3: Players in the dream team for WI vs Aus

Sl. no.	**Player name**	**Position**	**Team**
1	Shai Hope	Batsmen	West Indies
2	David Warner	Batsmen	Australia
3	Aaron Finch	Batsmen	Australia
4	Steve Smith	Batsmen	Australia
5	Jason Omar Holder	All rounder	West Indies
6	Jahmar Hamilton	Wicket keeper	West Indies
7	Kurtis Patterson	Batsmen	Australia
8	Pat Cummins	Bowler	Australia
9	Mitchell Starc	Bowler	Australia
10	Alzarri Joseph	All rounder	West Indies
11	Nathan Lyon	Bowler	Australia

5.2. Discussions

Some of the points observed are summarized as follows:

a. The proposed approach computes the points based on WSM which is then standardized so that there is less variation in the points computed.
b. The points of the players are totally based on their performance. The performance of the players for the last five years is taken into account where high weightage is given to the recent performance.
c. The performance of the players are extracted by the process of web scraping.
d. The proposed approach computes the weights of the factors by the cross-entropy method. The method is data driven and hence the weights of the factors are self-adjusted based on the performance of the players.
e. The player selection is done according to the GPP where the total points available for selecting the dream team is 100.

6. Conclusion and Future Scope

The comprehensive intention of the present paper is to develop a technique to select the best players to comprise the dream team abiding by certain rules and regulations. Although researchers have developed many models, very little effort has been given to develop a self-adjusted approach that is not only robust but also readjust its weight based on the recent performance of the players. In this regard, an integrated model is proposed. The proposed model integrates the cross-entropy and WSM with GPP. The model takes into account the performance of the players which are scraped from the www.espncricinfo.com api. The model gives high weightage to the recent performance of the players then to the latter. The weights of the factors are determined by the cross-entropy method. Unlike other weight computation methods, it is not dependent on the decision maker's view and also the method readjust the weight based on the performance of the players. To demonstrate the practicality of the proposed model a dream team is created for a match between India and New Zealand. The proposed model could be further improved by introducing additional variables such as the pitch reports, weather and injury data, which play a major role in formulating the structure of the team. The player performance against different teams considering home and away conditions could also be considered which is the future prospect of the current paper..

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