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ORIGINAL RESEARCH **OPEN ACCESS**

AN INDIVIDUAL-BASED TEAM RATING METHOD FOR T20 CRICKET

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ABSTRACT

Cricket is an ideal sport to isolate individual team member contribution with respect to winning. This is due to the volume of digital data available, combined with the relatively isolated nature of the batsman versus bowler contest observed per ball. Like many other sports, Cricket is reliant on the contribution of interacting individuals causing fluctuations in match outcomes. Understanding the quantifiable causes of this variation can help interested parties derive insight into team success and potential strategies for optimising performance. Understanding the individual dynamic within the team setting can lead to improved team ratings. The objective of this research was to develop a roster-based system for limited overs cricket by deriving a team rating as a combination of individual ratings. The intent was to build an adaptive optimisation system that selects a cricket team of 11 players from a list of available players, such that the optimal team produces the greatest team rating. The attributes used to define the individual ratings are based on the statistical significance and practical contribution to winning. An adaptive system was used to create the individual ratings using a modified version of a Product Weighted Measure. The weights for this system were created using a combination of a Random Forest and Analytical Hierarchical Process. The underlying framework of this system was validated by demonstrating an increase in the accuracy of predicted match outcomes compared to other established ranking methods for cricket teams. For the 2015/16 Big Bash, this approach outperformed the results outlined by Patel et al. (2016) by 12.3%. The results confirm that cricket team ratings based on the aggregation of individual playing ratings with attributes weighted towards winning limited over matches are superior to ratings based on summaries of team performances and match outcomes. This impact is highlighted by visualizing the variability of the ratings of Perth Scorchers during the 2015/2016 Australian Big Bash.

Keywords: Adaptive System, Product Weighted Measure, Analytical Hierarchical Process

INTRODUCTION

The growth of sport analytics and the need for meaningful sport related statistics has emerged in recent decades due to the popularity of professional sport as live and televised entertainment. This has led to increased investment in players and teams. The rise in player salaries and salary caps over the last 25 years provide ample evidence of the growth of sport analytics, with investors, franchises, clubs and other stakeholders wanting to determine the true value of their investment. For example, in the National Football League (NFL) there has been an increase of approximately 950% in player salaries since the 1980's, and an increase of 288% in salary cap since 1994 (Vroom, 2012). With global sports revenue estimated to grow by US$145.3 billion over the 2010-2015 period (Fenez & Clark, 2011) and the large investment of resources and the stakes involved, coaches and managerial staff cannot solely rely on subjective views and personal beliefs to make team and player selection decisions.

The explosion in the sporting industry in terms of popularity and revenue is evident in cricket. Cricket has seen huge global growth in revenue in recent years, and transformed into a sporting juggernaut due to the advent of T20 cricket. The Economist reported that global cricket will generate total revenues of approximately $2.5 billion over the period 2014-2022.

Given the variety of numerical data generated by sports, it is paramount that meaningful information is extracted from the data. There is a breadth of academic literature applying various statistical techniques to myriad sports. For example, Di Salvo *et. al.* (2010) utilised discriminant analysis to identify performance metrics that significantly distinguish between winning, losing and drawing teams in the Europe Champions League. Annis *et. al.* (2005) claimed that traditional win/loss and points scored ranking models applied to American Football fail to produce satisfactory rankings. The study therefore developed a hybrid paired comparison model which outperformed competitor models, producing robust results under model misspecification. Further, a modified least squares ranking procedure was developed in by Harville (2003) to rank division 1 American men's college basketball teams using game outcomes. The results showed that the predictive accuracy of the modified least squares (76.3%) method outperformed that of the basic least squares (74.2%).

Cricket has recently seen an exponential rise in the use of statistics to make informed and strategic decisions regarding player and team performance. Furthermore given the sports data rich environment and its increase in popularity over the past decade, cricket has recently seen an increase in analytical literature and the adoption of predictive methodologies at the professional level.

RESEARCH MOTIVATION

There is a scarcity in literature surrounding team rating systems utilising individual ability. This demonstrates a lack of demand and reflects a historical lack of access to data and computing resources. The primary objective was to develop a roster-based system for T20 cricket. The intent is to derive a meaningful, overall team rating using a combination of individual ratings from a playing eleven. The goal was to build an adaptive rating system that selects a cricket team, based on a set of criteria, from a playing squad, such that the team rating reflects the best chance of winning. For example if team A has a 15 'man' squad the system should select a cricket team which maximizes the team's overall rating, using individual ratings of the selected players, across a set of key roles and responsibilities. The optimal team was defined as the set of 11 individual players that produce the greatest probability of winning for team, i, against any given opponent, j. This should highlight the impact of star players returning to the team after injury or international duties.

It was hypothesised that a team rating system accounting for individual player abilities, outperforms systems that only consider macro variables such as home advantage, opposition strength and past team performances. This research centres on the development of an adaptive-predictive rating system, characterised by utilising past player performances, and accounting for the long and short term variability of a team's performance. An adaptive method was preferred as it updates player and team ratings "based on historic performances upon availability of data about current performances" (Leitner *et. al.*, 2010: 3). The assessment of system performance was observed through the prediction accuracy of future match outcomes, and benchmarked against the New Zealand Totalisator Agency Board (TAB) and CricHQ's predictive system (Bracewell *et. al.* 2014). The TAB was utilised as a benchmarking tool as it incorporates collective opinion and subjectivity to evaluate risk, while the CricHQ algorithm incorporates objective measures to evaluate risk.

The secondary objective was to ensure that the developed rating system accurately predicted match outcome (i.e. a system with high predictive power) and could outperform the predictive power of well-established and recognised predictive sporting algorithms. This serves as a validation of the primary research objectives.

There are five key components in the development of the adaptive rating system: The first component was the data. The second component was the significant performance metrics. The third component was the optimisation system. The fourth component was the individual player rating system. The fifth component was the models ability to generate the probability of winning.

Patel et al. (2016) explored the use of techniques outlined here, but noted an issue in evaluating the impact of bowlers who had not taken a wicket. Consequently, this paper extends the material presented in that paper by applying a reject inference method to calculate the inferred strike rate of non-wicket taking bowlers developed by Bracewell et al. (2016). Moreover this paper applies the rating algorithm to the Big Bash 2016 season as opposed to IPL 2015. This paper validates the reject inference methodology outlined in Bracewell et al. (2016) and expands on future model extension suggested in Patel et al. (2016).

INFERRED STRIKE RATE

A major issue with the individual rating system outlined in Patel et al. (2016) was the production of undefined ratings (i.e. N/A) for bowlers or all-rounders who have failed to take a wicket during a cricketing season. Given that a bowler's individual player rating is a function of strike rate, which is a function of wickets, a bowler who fails to pick up a wicket does not register a rating through the product weighted measure rating system. However failing to take a wicket does not mean the player failed to make a significant contribution to the team rating. This was reinforced by Patel et al. (2016) showing that three of the top 5 most important bowling metrics are geared around run restriction. Therefore if a bowler fails to take a wicket it does not mean they have failed to make a meaningful contribution to match outcome and overall team rating.

To overcome these model flaws this paper adopted the reject inference technique outlined in Bracewell et al. (2016). Bracewell et al. (2016) developed a method using reject inference techniques (commonly found in banking and finance journals to develop credit risk scorecards) to infer a strike rate given that the bowler did not pick up a wicket. The research found that dot balls, economy rate and balls bowled were significant indicators of a bowler’s wicket taking ability.

Adopting this methodology into the optimisation system framework it was found that the model classification accuracy increased from 65% to 73%. The updated system was 1. More indicative of talent and 2. Winners had an average winning probability of 54% while the older system (i.e. without inferred SR) had an average winner probability of 52%, providing a better distinction between winning and losing teams.

DATA

The analysis required end-of-match scorecard data for T20 cricket. Data was extracted from ESPNCricinfo (www.espncricinfo.com). An automated process using the SAS language was developed to extract and parse the scorecard data, and provide a convenient data structure. The developed system was tested on the Indian Premier League 2015. The scorecard data was split into a batting and bowling dataset outlining performance metrics, by player. Table 1 outlines the derived performance metrics and Table 2 provides definitions for each performance metric.

Table 1: Batting and Bowling Performance Metrics

Batting Metrics	Bowling Metrics
Batting Average	Economy Rate
Batting Strike Rate	Strike Rate
Average Contribution	Bowling Average
Percentage Boundaries Hit	Percentage Boundaries conceded
Runs Scored	Dot balls
Balls Faced	Balls Bowled
Total Boundaries	Percentage Dot
Sixes	Runs Conceded
Fours	Wickets
Games Played	Games Played
Number of Wins	Fours Conceded
Percentage Wins (Y)	Percentage Wins (Y)
	Sixes Conceded
	Number of Wins
	Total Boundaries
	Total Maidens

Table 2: Performance Metric Definitions

Performance Metrics	Definitions
Batting Average	Total runs divided by total dismissals
Total Dismissals	Number of times a batsmen been dismissed
Batting Strike Rate	Total runs divided by total balls
Percentage Boundaries (Bat)	Total boundaries divided by total balls faced
Batting Position	Position of the batting line-up a player occupies on average
Total Runs Scored	Total number of runs a batsmen has contributed to the batting side total
Balls Faced	Number of deliveries faced
Total Boundaries	Total fours hit + total sixes hit
Sixes Hit	Total number of balls hit over the field's boundary in the air
Fours Hit	Total number of balls hit over the field's boundary along the ground
Games Played	Total number of participated matches
Percentage Wins	Total number matches won divided by total number of matches played
Economy Rate	Total of runs conceded by overs bowled
Bowling Strike Rate	Total balls bowled divided wickets
Bowling Position	Position of the bowlers in the bowling line-up
Bowling Average	Total runs conceded divided by wickets
Percentage Boundaries (Bowl)	Total boundaries conceded divided by total balls bowled
Dot Balls	Total balls bowled in which no runs were conceded
Balls Bowled	Total number of deliveries by a bowler
Percentage Dots	Total dots divided by total balls bowled
Total Runs Conceded	Total number of runs contributed to the batting side
Total Wickets	Total number of batsmen a bowler has dismissed
Total Maidens	Total number of overs bowled in which no runs were conceded
Fours Conceded	Total number of balls bowled in which the ball was hit over the field's boundary along the ground
Sixes Conceded	Total number of balls bowled in which the ball was hit over the field's boundary in the air
Total Boundaries Conceded	Total fours conceded + total sixes conceded
Number of Wins	Total number of games won
Role	Identifies whether a player was batting or bowling
Player ID	Unique player identification number
Game ID	Unique match identification number
Team	The side in which a player resides

PERFORMANCE METRICS

Due to multicollinearity and high dimensionality, variable selection was paramount to minimise the presence of these effects and reduce the number of performance metrics that are implemented when evaluating individual player ratings. Given the multitude of performance metrics and research requirements to produce a highly predictive, practically meaningful, team rating system, an accurate means of assessing variable significance was critical for success.

A Random Forest technique was introduced to handle multicollinearity and complex interactions to identify performance metrics that significantly affect a player's contribution to team winningness. Random Forests "are a combination of tree predictors such that each tree on the values of a random vector sampled independently and with the same distribution for all trees in the forest" (Breiman, 2001: 5). Random Forests consist of a collection of uncorrelated and unpruned regression trees. Important performance metrics were derived in terms of winningness (i.e. proportion of wins).

Figure 1 illustrates the five most important metrics: strike rate, balls faced, batting average, total runs scored and percentage boundaries. Percentage boundaries (batsmen) is defined as total boundaries divided by total balls faced. Interestingly these important metrics are associated with scoring efficiency (i.e. strike rate and percentage boundaries), scoring consistency (i.e. batting average) and scoring volume (i.e. total runs scored).

Figure 2 Illustrates the five most important bowling metrics: economy rate, bowling average, strike rate, percentage boundaries and percentage dots. Interestingly, these important metrics are associated with wicket-taking efficiency (strike rate and bowling average) and run restriction (i.e. economy rate, percentage boundaries and percentage dots).

Figure 1: Batting Metric Random Forest Importance Plot

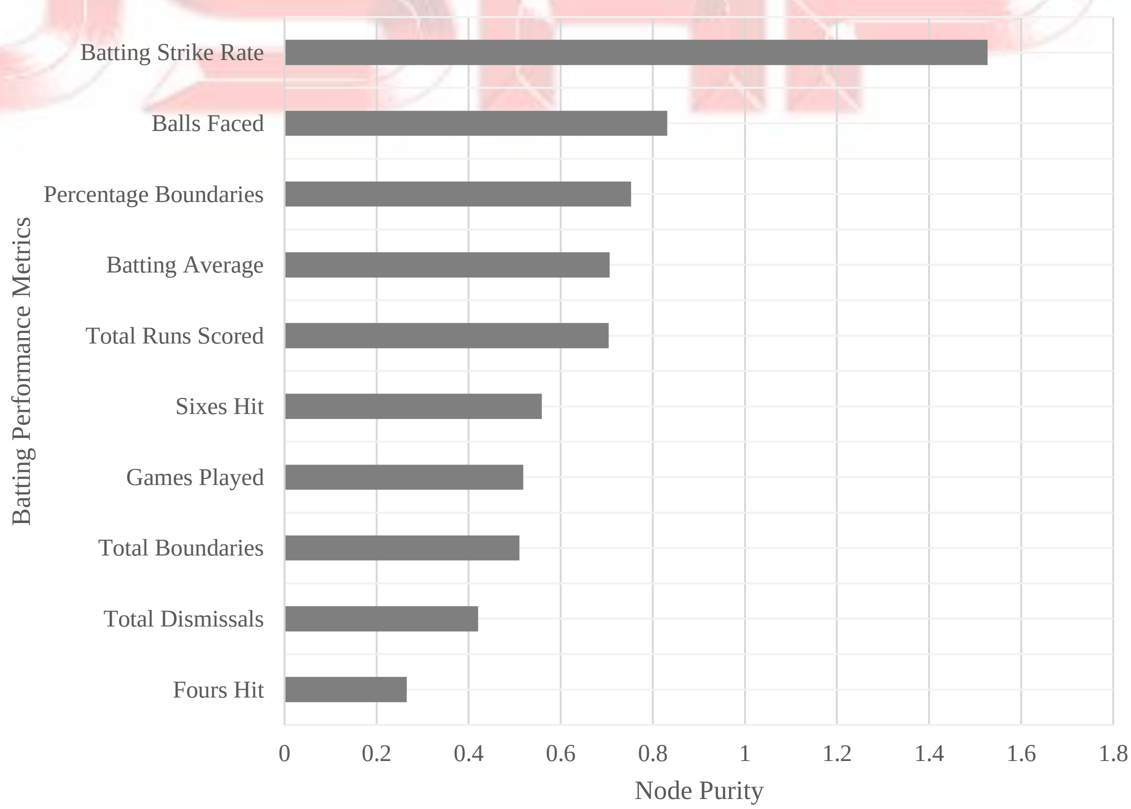
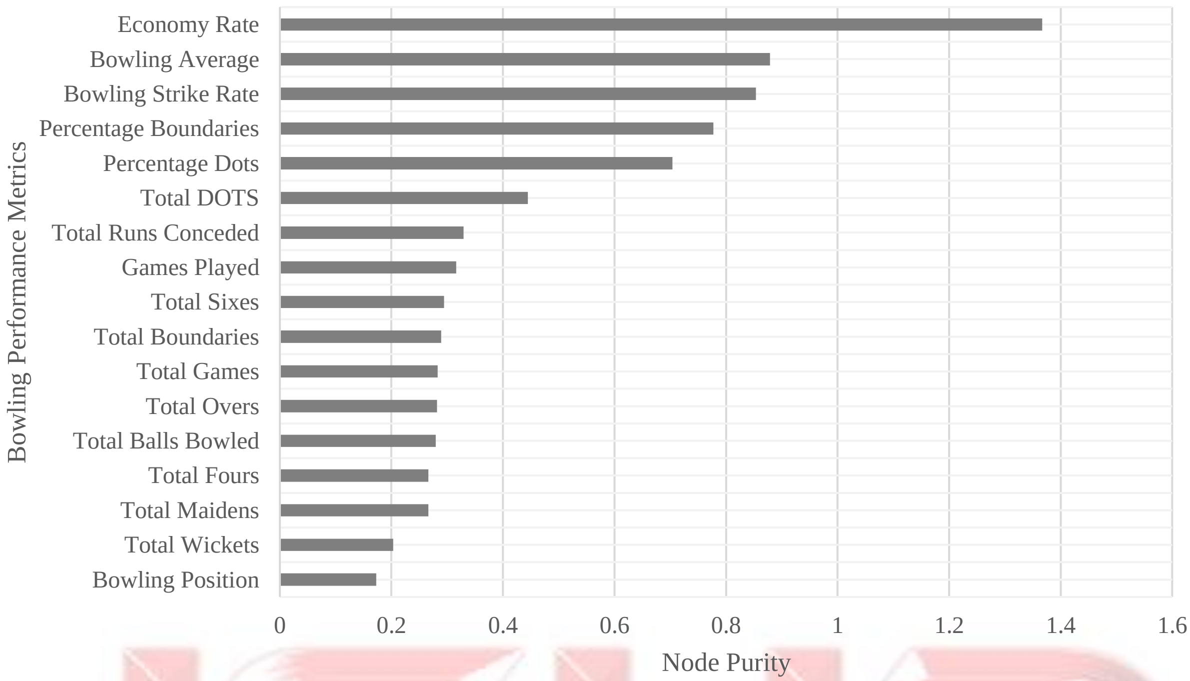


Figure 2: Bowling Metric Random Forest Importance Plot



Percentage boundaries (bowlers) is defined as total boundaries conceded divided by total balls bowled, while percentage dots is defined as total dots divided by total balls bowled. The results show that reducing the number of runs conceded and increasing the rate at which wickets are taken (i.e. efficiency) are significant to winningness.

BINARY INTEGER PROGRAMMING

Formally an optimisation algorithm is an "iterative numerical procedure for finding the values of the vector x that maximises or minimises the objective function $f(x)$ subject to constraints c" (Sargent, 2013: 100).

The optimisation method required the implementation of a binary decision variable, assigning a value = 1 to selected players and value = 0 otherwise (i.e. not selected). Since the adaptive rating system requires selecting players associated with the largest individual ratings, given a set of team and player-type constraints, a maximisation objective function is implemented. A Binary Integer Programming Model (BIPM) was adopted with the following framework:

The BIPM objective function:

$$Z = \sum_{i=1}^{n} \sum_{j=1}^{n_i} c_{ij} x_{ij} ,$$

where c_{ij} represents the player rating for player j in role i, $\{i = 1,2,3,4\}$,

$$where\ role\ i = \begin{cases} 1, if\ batting\ ability \\ 2, if\ bowling\ ability \\ 3, if\ all-rounder\ ability \\ 4, if\ wicket\ keeping\ ability \end{cases}$$

Decision Variable:

$$x_{ij} = \begin{cases} 1, if\ player\ j\ is\ selected\ for\ role\ i \\ 0, otherwise \end{cases}$$

The decision variable are binary identifiers for player-type i, ($i=1, 2, 3, and\ 4$), and player j, ($j=1, 2...n_i$).

The Binary Integer Programming technique utilises a Branch and Bound algorithm to solve the optimisation problem. The Branch and Bound algorithm "finds the optimal solution to an integer program by effectively enumerating the point in a sub-problem's feasible region" (Winston & Goldberg, 2004: 479). The algorithm searches the complete space of solutions for a given problem, for the best solution.

MODEL CONSTRAINTS

Performance metrics were aggregated on the 'team' variable. This manipulation step created a dataset containing both batting and bowling metrics at the *team level*.

Model constraints that accurately reflect a team's composition and the type of talent required to win T20 cricket matches were assessed. Team and player constraints were formulated. The constraints must take into account the number of batsmen, bowlers, all-rounders and wicket-keepers to build a cricket team of 11 players. Given that model constraints were team orientated rather than individual player constraints, performance metrics that contribute significantly towards winningness at the team level, as opposed to the individual level, were established. The constraints were formulated such that the 'optimal' team produces the greatest probability of winning. The importance of each performance metric on team winningness was established by applying the random forest technique.

Given the requirements of a cricket team the model constraints should follow the subsequent criteria:

<u>Construct Criteria:</u>

1. 11 players should be selected in the optimal team
2. Restrict players from being selected twice in the optimal team
3. A specific number of batsman should be selected in the optimal team
4. A specific number of bowlers should be selected in the optimal team
5. A wicket keeper should be selected in the optimal team
6. Select an all-rounder if the number of batsman, bowlers and wicket keepers exceed the allowable limits.

Applying a random forest technique to the dataset the top 10 important performance metrics, for T20 cricket, were: 1) batting strike rate, 2) total runs scored, 3) total fours hit, 4) percentage boundaries hit, 5) total boundaries hit, 6) batting average, 7) percentage boundaries conceded, 8) economy rate, 9) total dismissals and 10) total maidens.

The results (Figure 3) indicate that batting metrics were of greater importance than bowling metrics for winningness among T20 teams. The results showed that seven of the top ten metrics were batting orientated, and predominately geared around scoring efficiency (i.e. strike rate) and consistency (i.e. batting average). It was revealed that batsmen with high scoring efficiency and scoring consistency are necessary to increase a team's chance of winning a T20 cricket match. Moreover, the results indicate that the model constraints should be formulated such that the optimal team generated by the optimisation system has a greater batting focus than bowling focus. Additionally, it can be inferred that batting all-rounders are preferred over bowling all-rounders, for T20 cricket.

Figure 3: Team Level IPL Random Forest Importance Plot

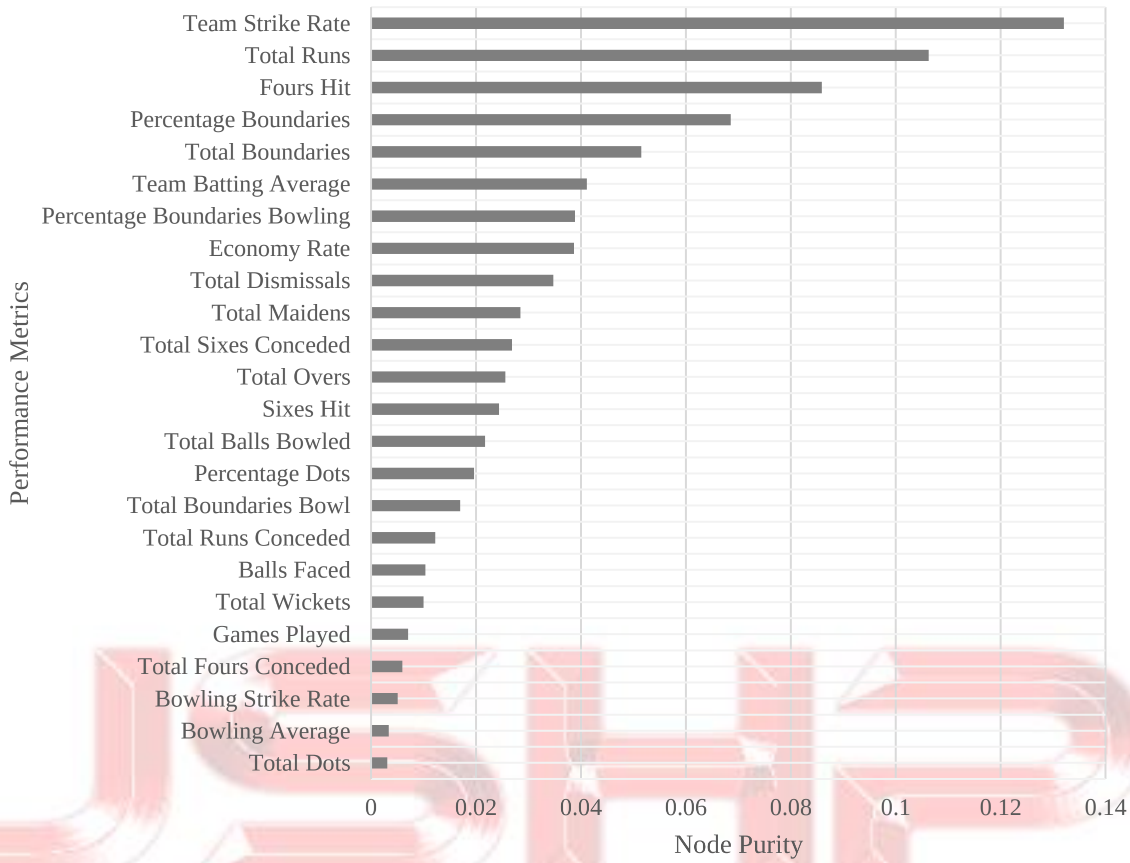


Table 3: Optimisation Model Constraints

Constraints	T20
Team	$\sum_{i=1}^{4}\sum_{j=1}^{n_1} x_{ij} = 11$
Player	$\sum_{i=1}^{4} x_{ij} \leq 1$
Batsman	$\sum_{j}(x_{1j} + x_{3j}) \geq 7$
Bowler	$\sum_{j}(x_{2j} + x_{3j}) \geq 4$
All-rounder	$\sum_{j} x_{3j} \geq 0$
Wicket-Keepers	$\sum_{j} x_{4j} = 1$

Table 3 outlines the model constraints. The constraints persuade the model to produce an optimal team with a heavy focus on batting ability as the model constraints require the optimal team to possess a greater number of batsmen than bowlers.

EVALUATING INDIVIDUAL PLAYER RATING SYSTEMS

Before filtering the individual player ratings through the BIPM the optimal individual rating system had to be identified. The optimal individual rating system is defined as the system that produces the greatest predictive accuracy, observed as the largest proportion of correct match outcomes when integrated into the adaptive system. The following three individual rating methods were benchmarked:

1. Analytical Hierarchy Process with Technical Order Preference by Similarity to Ideal Solution (AHP-TOPSIS) and Analytical Hierarchy Process with Complex Proportion Assessments (COPRAS)
2. Product Weighted Measure (PWM)
3. Principal Component Analysis (PCA)

Table 4 outlines the accuracy produced by the individual methods when implemented into the optimisation system.

Table 4: Adaptive System Accuracy

Adaptive System Results			
Competition	**PWM**	**AHP**	**PCA**
Big Bash League 2015	65%s	65%	35%

The results of the adaptive system utilising the PCA method produced the worst prediction accuracy because for majority of the matches the method was not applicable as a sufficient number of components failed to explain a sufficient amount of the variation. The component coefficients had a counter-intuitive direction effect. This resulted in ratings that laced practical significance.

Both the PWM and AHP-TOPSIS/ AHP-COPRAS produced the same predictive accuracy however the methods had a tendency to over-rate with strong performance. If a player had an abnormally good start to the season relative to the others within their player-type the ratings produced were too high. To counter this issue the performance metrics were scaled and bound between 0 and 1. Another flaw to the PWM was that it failed to produce ratings for all-rounders who only participated in either a batting or bowling capacity. It was found that during the early stages of a season each player only has a few opportunities to fulfil their role; for example an all-rounder may only need to bat or bowl, but not both. This creates situations where an all-rounder can significantly contribute towards a match outcome, but ratings are not produced as only one ability was utilized. This produced under-rated players and teams. To counter this issue the PWM was modified as follows:

1. If a batting all-rounder has not taken a wicket, during the season, the players batting rating, c_1, is regarded as their all-rounder rating.
2. If a bowling all-rounder has not batted, during the season, but did bowl, the players bowling rating, c_2, is regarded as their all-rounder rating.

As a validation method the modified PWM was applied to CPL and CWC2015 matches, the method offered slight improvements, predicting 74% and 82% of matches, respectively, outperforming the TAB and CricHQ algorithm.

Given these limitations a system was developed to address these issues. This included modifying the AHP and PWM method in order to produce better predictive accuracy. The AHP-TOPSIS/ AHP-COPRAS and PWM methods are explained in detail below.

EVALUATING INDIVIDUAL PLAYER AND TEAM RATINGS

The individual player rating method implemented into the adaptive rating system was a combination of the Product Weighted Measure and Analytical Hierarchy Process and Exponentially Weighted Moving Averages. The optimal {individual} rating method is defined as the system that produces the greatest predictive accuracy, observed as the largest proportion of correct match outcomes when integrated into the adaptive system.

The optimal team rating was calculated by aggregating individual player ratings of the selected players. This aggregation approach was justified in (Damodaran, 2006), stating that cricket is a sport characterised by one-on-one interactions between batsmen and bowlers, and that a players ability establishes the outcome of this interaction. Moreover the match outcome is defined by the interactions between batsmen and bowlers, therefore summing the individual player ratings provides a fair indication of team strength. Once ratings for team *i* and *j* have been calculated, the Bradley-Terry model was applied to calculate the probability of team *i* beating team j, $\pi_{i,j}$:

$$\pi_{i,j} = \frac{R_i}{R_i + R_j} \qquad \text{(Eq. 1)}$$

Leitner (2010) stated that the outcome of many sporting disciplines can be determined by pairwise comparisons, and that the outcome of a match or game is dependent on the current ability of the two teams. At the end of every match individual player ratings were updated and the optimal team rating, for each team, are reproduced, using the adaptive system (*adaptive system* = *optimisation system* + *individual ratings*). "This rating process represents an adaptive system as it updates player and team ratings based on historical performances upon the availability of data about current performances" (Leitner *et. al.*, 2010: 474).

PRODUCT WEIGHTED MEASURE

The Product Weighted Measure (PWM) was developed and applied by Croucher (2000) to rank batsmen, bowlers, wicket-keepers and all-rounders in international one day cricket. The method produces raw ratings for each player and then calculates the actual ratings relative to other players within their player-type. However the performance metrics implemented to rank the players were selected in an ad hoc manner and the weightings were subjectively chosen. Given the difference in importance of each performance metrics, a novel method was introduced which utilised the Analytical Hierarchy Process and Random Forest technique. This determined the appropriate weightings, α, for each important performance metric, for each player-type. The performance metrics implemented to rate individual player-types are outlined in Table 5.

Batsman ratings were calculated using equation 2 and 3:

$$U_{1j} = (Y_{1j}^{\alpha_1})(Y_{2j}^{\alpha_2})(Y_{3j}^{1-\alpha_1-\alpha_2}), \qquad \text{(Eq. 2)}$$

where U_{1j} represents the raw ratings for batsmen j using batting performance metrics Y_{1j} (total runs scored),Y_{2j} (percentage boundaries) and Y_{3j} (batting strike rate), while $\alpha_i's$ represents the importance weightings allocated to each performance metric. The raw ratings, U_{1j}, were then scaled to produce actual batsmen ratings relative to other batters in the league:

$$c_{1j} = \frac{U_{1j}}{\sum_{j=1}^{N} U_{1j}} \times n \ , \qquad \text{(Eq. 3)}$$

where n represents the number of batsmen in the competition.

Bowlers rating was calculated via equation 4:

$$U_{2j} = (Y_{4j}^{\alpha_1})(Y_{5j}^{\alpha_2})(Y_{6j}^{1-\alpha_1-\alpha_2}), \qquad \text{(Eq. 4)}$$

where U_{2j} represents the raw ratings for bowler j using bowling performance metrics, Y_{4j} (economy rate),Y_{5j} (percenatge boundaries) and Y_{6j} (bowling strike rate). The optimisation model outlined in the previous chapter incorporates a maximisation objective

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function and 'low' values of Y_{4j}, Y_{5j} and Y_{6j}, indicate 'good' bowlers. As such the U_{2j} values were scaled, such that higher values represent 'good' bowlers, using a technique outlined in Gerber & Sharp (2006):

1. $V_{2j} = K - \left(\frac{U_{2j}}{\sum_{j=1}^{n} U_{2j}}\right)$,

   where K is a positive value such that $K - \left(\frac{U_{2j}}{\sum_{j=1}^{n} U_{2j}}\right) > 0$
2. A bowler ratings were defined as: $c_{2j}^{1} = \frac{V_{2j}}{\sum_{j=1}^{n} V_{2j}} \times n_2$,

where n_2 represents the number of bowlers in a competition. This transformation ensures that higher ratings represent better bowlers.

Table 5: Pairwise Comparison Matrix by Player-type

Pairwise Comparison Matrix			
Batsman/Keepers	Strike Rate	Total Runs Scored	Batting Average
Strike Rate	1	1.25	1.15
Total Runs Scored	0.80	1	1.20
Batting Average	0.87	0.83	1
Bowlers	Economy Rate	Strike Rate	Percentage Boundaries
Economy Rate	1	1.25	1.15
Strike Rate	0.80	1	1.20
Percentage Boundaries	0.87	0.83	1
Batting All-Rounders	Strike Rate	Total Runs Scored	Batting Average
Strike Rate	1	1.25	1.15
Total Runs Scored	0.80	1	1.20
Batting Average	0.87	0.83	1
Bowling All-Rounders	Economy Rate	Strike Rate	Percentage Boundaries
Economy Rate	1	1.25	1.15
Strike Rate	0.80	1	1.20
Percentage Boundaries	0.87	0.83	1

Moreover, to ensure that the bowler ratings, c_{2j}^{1} had an equivalent variance compared to the batting ratings, the bowler ratings were scaled using a technique outlined in Croucher (2000):

$$c_{2j}^{p+1} = \left(c_{2j}^{p}\right)^{\frac{\sigma_{c_1}}{\sigma^{p}{}_{c_2}}}, \qquad \text{(Eq. 5)}$$

where σ_{c_1} and $\sigma^{p}{}_{c_2}$ represents the standard deviation of the batting ratings and standard deviation of the bowler ratings for the p^{th}iteration, respectively. To ensure equivalent spread of the batting and bowling ratings, equation 5 is an iterative process which stops when it has converged to an accepted lower limit, therefore $c_{2j}^{p+1} = c_{2j}$.

All-rounder ratings were calculated by multiplicatively combining their batting and bowling ratings:

$$c_{3j}^{1} = \left(c_{1j}^{\beta}\right)\left(c_{2j}^{1-\beta}\right), \qquad \text{(Eq. 6)}$$

where c_{1j} and c_{2j} represents the batting and bowling ratings, respectively, and β represents the weightings associated with the batting and bowling ratings. The scale adjusted measure (equation 8.5) was also applied to the all-rounder ratings, c_{3j} to ensure equivalent spread. A β weighting of 0.6 and 0.4 were assigned to batting (c_{1j}) and bowling (c_{2j}) ratings, respectively, because batting ability is of greater importance than bowling ability in T20 cricket, as shown in section 3.

Wicket keepers were treated as batsmen and therefore their ratings were calculated using equations 2 and 3. Due to data limitations wicket keeper metrics such as byes and catches could not be utilised to derive ratings.

ANALYTICAL HIERARCHY PROCESS

The Analytical Hierarchy Process (AHP) is a multi-criteria decision making tool developed by Thomas Saaty (1987). Given a user defined pairwise comparison matrix, the AHP translates the matrix into a vector of relative weights for each criterion element using a mathematical model. The pairwise comparison matrix provides a numerical comparison of each attribute with respect to the other attributes being evaluated. These matrix entries are determined using the fundamental AHP scale and are based on prior experience or expert knowledge. Applying the AHP to the pairwise comparison matrix translate the subjective weights into objective weights, representing the importance of the attribute relative to the other attributes. Moreover the method implements a consistency measure for each attribute to ensure that the 'user' defined weights are consistent and reduces bias in the decision making process.

An AHP-TOPSIS method was applied to rate batsman, bowlers and wicket-keepers. TOPSIS is a multi-criteria decision making tool which evaluates various options based on their similarity to the optimal solution by generating weights using the AHP and loading weights into the TOPSIS process. The TOPSIS (Technical Order Preference by Similarity to Ideal Solution) method finds solutions from a finite set of alternatives that simultaneously minimise the distance from the ideal solution and maximises the distance from a negative ideal solution. The basic principle is that the chosen alternative should have the shortest distance from the ideal solution and the farthest distance from the negative-ideal solution. The positive ideal solution was applied to rate batsman and wicket keepers since their performance metrics were benefit criteria (i.e. higher values represent better batsman). The negative ideal solution was applied to rate bowlers since their performance metrics were cost criteria (i.e. lower values represent better bowlers). The idea is to increase benefits and reduce costs.

An AHP-COPRAS method was applied to rate all-rounders. The COPRAS (Complex Proportion Assessments) method is a decision making tool utilised to evaluate both maximising and minimising criteria values (i.e. performance metrics). Given these aspects the technique was applied to all-rounders, as both batting (i.e. benefit criteria) and bowling (i.e. cost criteria) performance metrics identify an all-rounders ability. The idea is to maximise batting metrics and minimise bowling metrics.

RANDOM FOREST + AHP WEIGHTINGS

The system for determining the appropriate PWM weightings, α, is outlined as follows:

1. Identify the order of importance for each performance metric, by player-type, for T20 cricket. The order of importance for each performance metric is established by the random forest (RF) importance plot, by player-type.

2. Use the RF order of importance plot to create an $n \times n$ pairwise comparison matrix, for each player-type, where each entry, a_{ij} represents the importance of criteria i with respect to j. The relative importance of each performance metric, a_{ij}, follows the logic (i.e. importance order)

established by the random forest importance plot. For example, if percentage boundaries are of greater importance to winningness than batting average, among batsmen, the relative importance of percentage boundaries vs. batting average > 1. A pairwise comparison matrix was produced for each player-type and their associated performance metrics. The pairwise comparison matrices are outlined in table 5), for each player-type.

The order of importance for each performance metric was established through the Random Forest importance plot (Figure 3). The AHP pairwise comparison matrices for each player-type were developed by former first-class cricketer Jason Wells (73 First class matches and 81 List A games between 1989 and 2001).

3. Run the AHP on the pairwise comparison matrices and generate the weights associated with each performance metric for each player-type. The weights generated can be found in table 6.

These weights align with findings established above, stating that a winning T20 team requires players with high scoring efficiency, high scoring consistency and high run restricting ability. Table 6 shows that performance metrics such as batting strike rate, total runs scored and economy have a greater weighting relative to other metrics.

Table 6: Weightings for T20 Cricket Performance Metrics

Performance Metrics	Batsmen	Bowlers	All-rounders	Wicket-Keepers
Total Runs Scored	0.33	-	0.34	0.33
% Boundaries (batting)	0.30	-	0.30	0.30
Batting Strike Rate	0.37	-	0.36	0.37
% Boundary (bowling)	-	0.33	0.35	-
Bowling Strike Rate	-	0.30	0.27	-
Economy Rate	-	0.37	0.38	-

OPTIMAL TEAM COMPARED TO SELECTED TEAM

Applying the adaptive rating system to the IPL 2015 competition, highlighted that on occasion the optimal team generated by the optimisation model would differ from that selected by coaches and managers meaning the ‘optimal’ team rating would not always be the playing team. To counter this issue, the player ratings of the selected players were aggregated to generate a team rating. This provides an indication of team strength. Importantly, the accuracy of the predictions reinforces this method of creating team rating.

FORECASTING METHOD

Since the PWM ratings are generated relative to the sum of the other ratings, for a given player-type, this enables the ability to track player performance on a match-by-match basis, and assesses a player’s progression as the season matures. This increases the adaptive nature of the developed rating system. The time-stamped ratings enabled the application of forecasting methods to player ratings.

Daniyal *et al.* (2012) applied Exponentially Weighted Moving Average (EWMA) control charts to individual batting performances. The study results appeared to produce sensible performance predictions. An area for future research is exploring optimal forecasting methods. Exponential smoothing was applied by Clarke (2011) to predict tennis player ratings. Bracewell and Ruggiero (2009) utilised control charts to monitor batting performances of New Zealand domestic cricketers, and established that control charts such as EWMA accurately forecasted a batsmen's form.

EWMA

According to Steiner (1999) the formal definition for EWMA test statistic is given by:

$$z_t = \alpha \bar{x}_t + (1-\alpha) z_{t-1} \ , \qquad \text{(Eq. 7)}$$

where is a constant weight, representing the level of importance placed on current observations, $\bar{x}_t$ is the sample mean at time t, and z_{t-1} is the test statistic from time $t-1$. "Exponentially Weighted Moving Averages (EWMA) are known for exhibiting optimal properties for some forecasting and quality control applications" (Steiner, 1999: 1). The technique averages the data and allocates less and less importance to older observations. In the context of this research EWMA is adopted to forecast player and team ratings and measure their quality (i.e. form).

SYSTEM ACCURACY

The EWMA methodology was embedded into the PWM individual rating method with a weighting measure, α, of 0.72. This method predicts a players rating for the following match, and filters the predicted ratings through the optimisation system to generate a forecasted team rating. Team ratings were then used to calculate the probability of winning using the Bradley-Terry model (equation 1). Applying this method to the Big Bash 2015/16 gave a 12.3% improvement in predictive accuracy (65% vs. 73%) over Patel et al. (2016) method.

SEASON TRACKING

An application of the method outlined throughout this paper is the ability to track season performance by team and identify the direct effect of an international player/ injured arriving back to the team. Note these ratings were calculated after 10 BBL matches had been played in order to generate appropriate ratings and early season poor performances.

Figure 4: Scorchers 2016 Big Bash Season

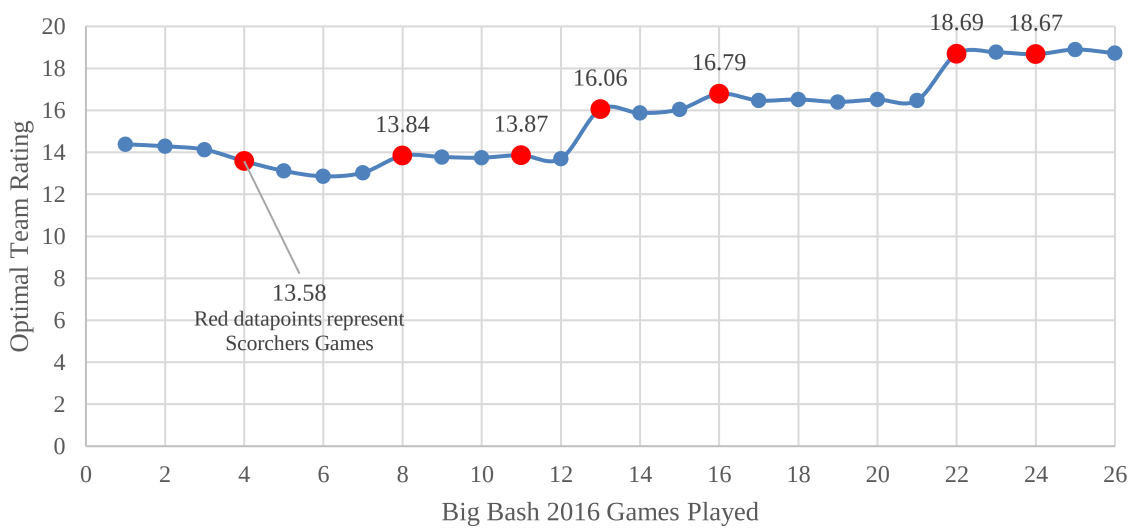

Figure 4 tracks season progress of the Perth Scorchers in the 2016 Big Bash competition. The step change from game 12-13 in team rating occurred when the Perth Scorchers played Adelaide and won by 10 wickets. Additionally SE Marsh scored 76 runs off 54 balls, JP Behrendorff took 3 wicket for 26 runs off 4 overs and AJ Tye took 2 wickets for 25 runs off 4 overs. Overall this was a strong team performance by the Scorchers and as such the model was able to pick on the quality performance and appropriately increase their ratings. Additionally SE Marsh joined the Scorchers in Game 13; the presence of an international player improved the team rating.

Going into the postseason the model ranked Perth has the third ranked team behind the Melbourne Stars and Sydney Thunder. Consequently Perth was knocked out of the semi-finals by the Melbourne Stars, who lost to the Sydney Thunder in the finals.

DISCUSSION AND CONCLUSION

Given cricket's exponential growth into a multi-billion dollar industry, it has become more critical than ever to introduce analytical methods for team selection. The adaptive system is useful for decision making among coaching and managerial staff, in terms of player selection, and can be implemented to identify the optimal team for T20 cricket.

The lack of academic literature surrounding team rating systems utilising individual ability within cricket, the absence of the application of predictive techniques to forecast match outcome and the growing popularity of sports betting, established an entry point in the market for this research.

This research developed a roster-based optimisation system for T20 cricket by deriving a meaningful, overall team rating using a combination of individual ratings from a playing eleven. The research revealed that an adaptive rating system accounting for individual player abilities, outperforms systems that only consider macro variables such as home advantage, opposition strength and past team performances. The assessment of system performance was observed through the prediction accuracy of future match outcomes.

The adaptive rating system was applied to the Big Bash League 2016, and the systems predictive accuracy was benchmarked against the New Zealand Totalisator Board Agency (TAB) and the CricHQ algorithm.

The results revealed that the developed rating system outperformed the TAB and CricHQ algorithm by 26% and 18%, respectively. The result demonstrates that cricket team ratings based on the aggregation of individual player ratings are superior to ratings based on summaries of team performances and match outcomes; validating the research hypothesis. This demonstrated that rating systems that consider micro variables generate greater predictive accuracy than systems that only consider macro variables.

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