TACTICS FOR TWENTY20 CRICKET

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Abstract: This paper explores two avenues for the modification of tactics in Twenty20 cricket. The first idea is based on the realisation that wickets are of less importance in Twenty20 cricket than in other formats of cricket (e.g. one-day cricket and Test cricket). A consequence is that batting sides in Twenty20 cricket should place more emphasis on scoring runs and less emphasis on avoiding wickets falling. On the flip side, fielding sides should place more emphasis on preventing runs and less emphasis on taking wickets. Practical implementations of this general idea are obtained by simple modifications to batting orders and bowling overs. The second idea may be applicable when there exists a sizeable mismatch between two competing teams. In this case, the weaker team may be able to improve its win probability by increasing the variance of run differential. A specific variance inflation technique which we consider is increased aggressiveness in batting.

1. Introduction

Twenty20 cricket is the most recent format of cricket. It was introduced in 2003, and gained widespread acceptance with the first World Cup in 2007 and with the introduction of the Indian Premier League in 2008. The main difference between Twenty20 cricket and the more established format of limited *overs* cricket known as one-day cricket is that the former is based on a maximum

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of 20 overs of batting whereas the latter is restricted to a maximum of 50 overs of batting. Consequently, Twenty20 cricket has a shorter duration of play than one-day cricket, and this is appealing to those with limited time to follow sport. Because the two formats of cricket are so similar, it appears that many of the practices of one-day cricket have transferred to Twenty20 cricket. For example, although there are critics (Perera and Swartz, 2013), the Duckworth-Lewis method for resetting targets in interrupted one-day cricket matches is also used in Twenty20 cricket. As another example, it is often the case that a nation's Twenty20 side will resemble its one-day side even though there are different skill sets required in the two formats of cricket.

Since Twenty20 cricket is a relatively new sport, it may be the case that optimal strategies have not yet been fully developed, and instead, Twenty20 cricket is played in much the same way as one-day cricket. This paper explores two avenues for the modification of tactics in Twenty20 cricket which may provide competitive advantages to teams. Of course, with the universal adoption of strategies by all teams, advantages cease to exist. This is one of the themes discussed in the novel "The Blind Side: Evolution of the Game" (Lewis, 2006) which was later popularised as a motion picture starring Sandra Bullock.

The first avenue for improving tactics in Twenty20 cricket is based on the realisation that *wickets* are of less importance in Twenty20 cricket than in other formats of cricket (e.g. one-day cricket and Test cricket). A consequence is that batting sides in Twenty20 cricket should place more emphasis on scoring runs and less emphasis on avoiding wickets falling. On the flip side, fielding sides should place more emphasis on preventing runs and less emphasis on taking wickets. To justify the claim that wickets are of less importance in Twenty20 cricket than in one-day cricket, Table 1 provides a wicket comparison between Twenty20 cricket ($n = 243$ matches) and one-day cricket ($n = 835$ matches) based on international matches involving full member nations of the ICC (International Cricket Council). The matches were played during the period of February 17, 2005 through December 25, 2013. We see in Table 1 that batting reaches the 8th batsman (i.e. 6 or more wickets taken) 84% of the time in one-day cricket but only 65% of the time in Twenty20 cricket. Since the 8th, 9th, 10th and 11th batsmen tend to be weaker batsmen, we observe that weak batsmen are batting less often and that teams rarely (10% of the time) expend all of their wickets in Twenty20 cricket. Since we are less concerned with wickets, it follows that a potential strategy for Twenty20 batting is to ensure that batsmen with high *strike rates* bat early in the batting lineup. Conversely, it may make sense for the bowling team to prevent runs by introducing bowlers with low *economy rates* early in the bowling order.

Table 1: Proportion of first innings with x or more wickets taken when the innings terminate, $x = 5, 6, \ldots, 10$.

	Proportion of first innings with x or more wickets taken when the innings terminate					
	$x = 5$	$x = 6$	$x = 7$	$x = 8$	$x = 9$	$x = 10$
Twenty20	0.84	0.65	0.45	0.27	0.17	0.10
One-Day	0.94	0.84	0.73	0.58	0.44	0.29

To emphasize the distinction between Twenty20 cricket and one-day cricket involving wicket usage, Table 2 considers the same time frame as Table 1 and shows the distribution of wickets taken after 90% of the overs are used. In Table 2, all Twenty20 first innings were considered that reached the end of the 18th over (i.e. 90% of the maximum number of overs). For one-day cricket, we considered all first innings that reached the end of the 45th over (i.e. 90% of the maximum number of overs). From these stages of a match, we again see that late-order batsmen bat less often in Twenty20 cricket than in one-day cricket.

Table 2: Proportion of first innings with x or more wickets taken at the time when 90% of the overs are completed, $x = 5, 6, \ldots, 10$.

	Proportion of first innings with x or more wickets taken when 90% of the overs are completed					
	$x = 5$	$x = 6$	$x = 7$	$x = 8$	$x = 9$	$x = 10$
Twenty20	0.66	0.37	0.20	0.09	0.04	0.01
One-Day	0.76	0.54	0.35	0.24	0.14	0.09

The second avenue for improving tactics is motivated by Figure 1 which plots the distribution of the amount by which Team A defeats Team B. This is a general density plot that is applicable to many sports where “amount” could represent runs, goals, points, time, etc. We have made the distribution symmetric although this is not required. We have also created the plot so that Team A is much stronger than Team B, and on average, Team A will win by a considerable amount under standard tactics. The probability that Team B wins corresponds to the area under the density curve to the left of zero. There is a second distribution displayed in Figure 1 where Team B has modified its tactics so as to increase the variance of the response variable. It is possible that this change of tactics will result in Team B losing on average by an even greater amount (i.e. the mean of the distribution is shifted to the right). However, our emphasis is on left tail probabilities corresponding to negative values. These are the cases in which Team B wins. What we see in Figure 1 is that Team B wins more often under modified tactics with increased variance than under standard tactics. In this paper, we explore tactics with inflated variance which may allow a weaker team in Twenty20 cricket to win more often.

In Twenty20 cricket, the quantity of interest that leads directly to wins and losses is run differential. When a team scores more runs than its opposition, they win the match. To investigate run differential, the study of historical matches between two teams is of little value. The composition of the teams change from match to match, and there is rarely a sufficient match history between two teams from which to draw reliable inferences. In addition, matches from the distant past are irrelevant in predicting the future. We therefore use simulation techniques under altered tactics to investigate the distribution of run differential.

In Section 2, we provide an overview of the match simulator developed by Davis, Perera and Swartz (2015). The simulator is the backbone for investigating run differential. For the casual reader, this section can be skimmed, as it is only important to know that methodology has been developed for realistically simulating Twenty20 matches. In Section 3, we consider modified batting orders. The proposal is to load the batting order so that batsmen with higher strike rates bat earlier in the batting order. This idea aligns with the theme that wickets are less important in Twenty20 cricket than in one-day cricket. In Section 4, we consider modified bowling orders. The proposal is that bowlers with low economy rates should bowl early in the bowling lineup. This idea also aligns

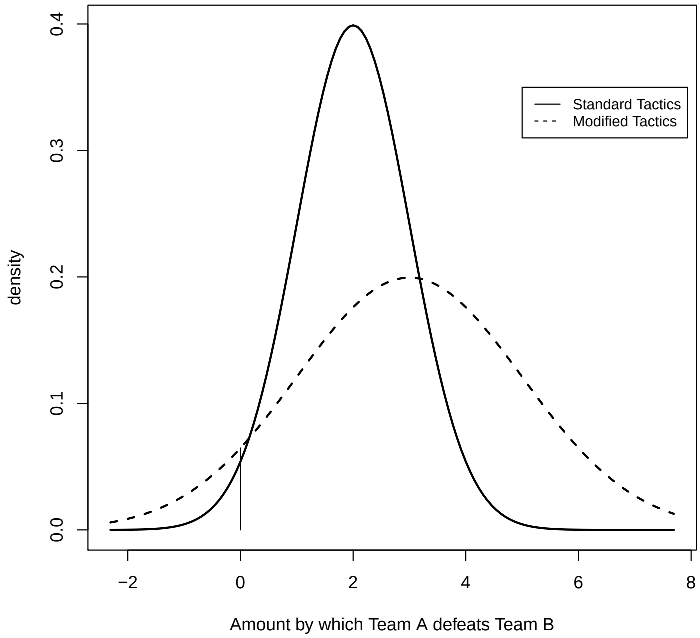

Figure 1: Probability density functions of the amount by which Team A (the stronger team) defeats Team B (the weaker team). The tail regions to the left of zero correspond to matches where Team B wins.

with the theme that wickets are less important in Twenty20 cricket than in one-day cricket. Here, our focus is to suppress runs rather than be concerned with taking wickets. In Section 5, we increase the aggressiveness of batsmen. This has the dual effect of increasing run scoring while simultaneously increasing the rate of wickets falling. This is clearly a variance inflation technique. In Section 6, we consider a more comprehensive strategy involving modified batting and bowling orders. Here we use a simulated annealing algorithm over the vast combinatorial space of lineups (i.e. team selection, batting order and bowling order) so as to maximise win percentage. This approach is based on ideas from Perera, Davis and Swartz (2016). We conclude with a short discussion in Section 7.

The exploration of tactics appears to be a novel exercise for cricket generally, and Twenty20 cricket in particular. Clarke (1998) recommends that teams should score more quickly in the first innings in one-day cricket than is the current practice. Swartz (2016) provides a survey of cricket analytics with some discussion devoted to tactics and strategy.

2. Overview of simulation methodology

We now provide an overview of the match simulator developed by Davis et al. (2015) which we use for the estimation of the run distribution for a given team. In cricket, there are 8 broadly defined outcomes that can occur when a batsman faces a bowled ball. These batting outcomes are listed below:

$$\begin{aligned} \text{outcome } j=0 &\equiv \text{0 runs scored} \\ \text{outcome } j=1 &\equiv \text{1 runs scored} \\ \text{outcome } j=2 &\equiv \text{2 runs scored} \\ \text{outcome } j=3 &\equiv \text{3 runs scored} \\ \text{outcome } j=4 &\equiv \text{4 runs scored} \\ \text{outcome } j=5 &\equiv \text{5 runs scored} \\ \text{outcome } j=6 &\equiv \text{6 runs scored} \\ \text{outcome } j=7 &\equiv \text{dismissal} \end{aligned} \tag{1}$$

In the list (1) of possible batting outcomes, *extras* such as *byes*, *leg byes*, *wide-balls* and *no balls* are excluded. In the simulation, extras are introduced by generating occurrences at the appropriate rates. Extras occur at the rate of 5.1% in Twenty20 cricket. The outcomes $j=3$ and $j=5$ are rare but are retained to facilitate straightforward notation.

According to the enumeration of the batting outcomes in (1), Davis et al. (2015) suggested the statistical model:

$$(X_{iow0},\ldots,X_{iow7}) \quad \sim \quad \text{multinomial}(m_{iow};\; p_{iow0},\ldots,p_{iow7}) \tag{2}$$

where X_{iowj} is the number of occurrences of outcome j by the ith batsman during the oth over when w wickets have been taken. In (2), m_{iow} is the number of balls that batsman i has faced in the dataset corresponding to the oth over when w wickets have been taken. The dataset was special in the sense that it consisted of detailed ball-by-ball data. The data were obtained using a proprietary parser which was applied to the commentary logs of matches listed on the CricInfo website (www.espncricinfo.com).

The estimation of the multinomial parameters p_{iowj} in (2) is a high-dimensional and complex problem. The complexity is partly due to the sparsity of the data; there are many match situations (i.e. combinations of overs and wickets) where batsmen do not have batting outcomes. For example, bowlers typically bat near the end of the batting order and do not face situations when zero wickets have been taken.

To facilitate the estimation of the multinomial parameters, Davis et al. (2015) introduced parametric simplifications and a hybrid estimation scheme using Markov chain Monte Carlo in an empirical Bayes setup. A key idea of their estimation procedure was a bridging framework where the multinomial probabilities in a given situation (i.e. over and wickets lost) could be estimated reliably from a "nearby" situation.

Given the estimation of the parameters in (2) (see Davis et al., 2015), first innings runs can be simulated for a specified batting lineup facing an average team. This is done by generating multinomial batting outcomes in (1) according to the laws of cricket. For example, when either 10 wickets are taken or 20 overs are bowled, the first innings is terminated. Davis et al. (2015) also provided modifications for batsmen facing specific bowlers (instead of average bowlers), accounted for the home field advantage and provided adjustments for second innings batting.

3. Modified batting orders

In Twenty20 cricket, the objective is to score more runs than your opponent. To maximise runs scored, it is important to carefully consider team selection, and once a team is selected, to determine a good batting order (Perera et al., 2016). The criterion "good" is not straightforward as the consensus opinion is that you want batsmen at the beginning of the batting lineup who both score runs at a high rate but are dismissed at a low rate. Recall that batting in the first innings of a Twenty20 match concludes when either 20 overs have been completed or when 10 wickets have been lost.

However, we have argued that wickets are of less importance in Twenty20 cricket than in the more established one-day format. We therefore consider an extremely simple idea of altering the batting order such that batsmen with high strike rates (average runs per 100 balls) bat early in the batting lineup.

At the time of writing, India may be regarded as one of the stronger Twenty20 sides and we consider their batting order as given in Table 3. This was the batting order used in their January 31, 2016 match versus Australia where India won by 7 wickets with 0 balls remaining. As an opponent, we consider Bangladesh which is well-known to be a weaker side. In the 2016 Twenty20 World Cup, Bangladesh were placed in the group stage consisting of eight teams, from which two teams advanced to the Super 10 stage. We consider Bangladesh's Twenty20 batting lineup from January 17, 2016 where they defeated Zimbabwe by 42 runs. Based on repeated match simulations with these lineups, we see from Table 3 that Bangladesh is expected to defeat India only 21% of the time. The simulated matches were carried out in a simple way; we generated first inning runs for both India and Bangladesh, and then calculated the run differential to determine the match winner.

Table 3: Batting orders used in the match simulator for India versus two Bangladesh lineups. The career Twenty20 strike rates for the Bangladesh batsmen are given in parentheses. Summary statistics regarding the simulation are given at the bottom.

India (Jan 31, 2016)	Bangladesh (Jan 17, 2016)	Bangladesh (alternative)
01. RG Sharma	T Iqbal	S Al Hasan (132.6)
02. S Dhawan	S Sarkar	S Sarkar (130.6)
03. V Kohli	S Rahman	S Rahman (119.0)
04. SK Raina	M Mahmudullah Riyad	T Iqbal (117.1)
05. Y Singh	M Rahim	M Rahim (115.9)
06. MS Dhoni	S Al Hasan	M Mahmudullah Riyad (107.3)
07. HH Pandya	S Hom	M Mortaza (104.6)
08. RA Jadeja	N Hasan	N Hasan
09. R Ashwin	M Mortaza	S Hom
10. JJ Bumrah	A-A Hossian	A-A Hossian
11. A Nehra	M Rahman	M Rahman
	Win Pct = 21%	Win Pct = 37%
	Mean(Run Diff) = -22.1	Mean(Run Diff) = -10.0
	StdErr(Run Diff) = 28.6	StdErr(Run Diff) = 30.0

What we further observe in Table 3 are the strike rates corresponding to the Bangladesh batsmen (we ignore the four pure bowlers). We therefore consider an alternative batting order that Bangladesh has never utilised in practice. In the alternative lineup, we place the Bangladesh batsmen in decreasing order according to their career strike rates based on international and IPL data up to October 25, 2015. The biggest changes involves Shakib Al Hasan who moves from batting position #6 to position #1, and Tamin Iqbal who moves from position #1 to #4. With these radical changes, we observe a huge improvement for Bangladesh who now win 37% of the time via the simulation procedure. We note that Al Hasan is an explosive batsmen and the Jan 17, 2016 lineup does not take advantage of his run scoring capability. In Twenty20 cricket, it is sometimes the case that the 6th batsman in an order may not have the opportunity to bat. We also note that Iqbal is an experienced player, and perhaps his longstanding tenure and reputation plays a role in his batting position with Bangladesh. In Table 3, we also observe that the standard lineup used by Bangladesh would have 22.1 fewer average first innings runs than India. When the Bangladesh lineup is altered with the highest strike rate batsmen at the beginning of the batting order, the mean run differential is reduced to 10.0 runs.

The results in Table 3 are stunning, and this is particularly due to the batting placement of Al Hasan. Other teams may not be able to have such dramatic improvements. It depends on whether or not their standard lineups use high strike rate batsmen near the beginning of the batting order. Also, we have used career strike rate as a criterion for batting order. This may not be optimal as we note that a batsman's batting position in his team impacts how freely he can bat which in turn affects his strike rate.

4. Modified bowling orders

From the bowling perspective, we now consider how a fielding team can suppress runs. We again use the sample case from Section 3 involving a hypothetical match between Bangladesh and India, and we consider bowling from the perspective of Bangladesh.

In Table 4, we provide the bowling order that was used by Bangladesh in their recent January 17, 2016 match against Zimbabwe. We observe that they used six bowlers in the match. If this bowling order is used against the India lineup listed in Table 3, we recall from the simulation procedure that Bangladesh wins only 21% of the time and has an average deficit in run differential of 22.1 runs.

We now consider what would happen if Bangladesh's batting order was left unchanged from January 17, 2016 but we require that the five bowlers (M Rahman, S Al Hasan, A-A Hossain, M Mortaza and S Rahman) bowl in the order of increasing economy rate. In other words, each would bowl four consecutive overs in the specified order. This idea aligns with the theme that wickets are less important in Twenty20 cricket than in one-day cricket. We note that the proposed bowling order is unrealistic as teams are required to change bowlers between overs and teams strategise concerning the utilisation of spin and fast bowlers. However, using the proposed bowling order in our simulation procedure, the Bangladesh win rate increases from 21% to 24% and the average run differential deficit improves from 22.1 runs to 20.1 runs.

Although the results above are not as dramatic as with the modified batting orders in Section 3, this may be due to the fact that the Bangleshi bowlers have comparable economy rates. For teams with greater disparities in their bowling economy rates, the modification of bowling orders may yield greater improvements. Also, suppose that you had three bowlers with comparable economy rates. You would not need to have them bowl in the order ABCABCABCABC, for example. They could bowl in alternative orders such as CBACBACBACBA.

Table 4: Bowling order used by Bangladesh in their January 17, 2016 match versus Zimbabwe. Career economy rates are given in parentheses based on international and IPL data up to October 25, 2015. Shuvagata Hom's economy rate is not listed as this was his first international Twenty20 match where he bowled.

Ball	Bowler	Ball	Bowler
0.1-0.6	S Hom	10.1-10.6	S Rahman
1.1-1.6	S Al Hasan (7.20)	11.1-11.6	S Al Hasan
2.1-2.6	A-A Hossain (7.74)	12.1-12.6	M Mortaza
3.1-3.6	M Rahman (6.03)	13.1-13.6	S Al Hasan
4.1-4.6	M Mortaza (8.46)	14.1-14.6	M Mortaza
5.1-5.6	M Rahman	15.1-15.6	A-A Hossain
6.1-6.6	M Mortaza	16.1-16.6	M Rahman
7.1-7.6	S Al Hasan	17.1-17.6	A-A Hossain
8.1-8.6	S Rahman (8.52)	18.1-18.6	S Hom
9.1-9.6	S Hom	19.1-19.5	M Rahman
		19.6	S Rahman

5. Increased aggressiveness

In this section, we explore the idea of variance inflation by increasing the aggressiveness of batsmen. For implementation of this idea, we recognise that batsmen are more aggressive when fewer wickets have been taken. We therefore define *wicket shift behaviour* (WSB) of -1 as a modification in batting style as if one fewer wicket had been taken. In other words, let the state of the match (o, w) correspond to the oth over when w wickets have been taken. Then wicket shift behaviour of -1 corresponds to

- during $(o, w = 0)$, modify batting behaviour as though the state were $(o, w = 0)$
- during $(o, w = 1)$, modify batting behaviour as though the state were $(o, w = 0)$
- during $(o, w = 2)$, modify batting behaviour as though the state were $(o, w = 1)$

  $\vdots$ $\vdots$
- during $(o, w = 9)$, modify batting behaviour as though the state were $(o, w = 8)$

We similarly define wicket shift behaviours of $-2, -3, \ldots, -9$ which correspond to increasing levels of batting aggressiveness. It is also possible to define non-integer levels of wicket shift behaviour. For example, with respect to a given ball, wicket shift behaviour of -1.2 corresponds to wicket shift behaviour of -1 with probability 0.8 and wicket shift behaviour of -2 with probability 0.2.

The proposed batting schemes are well-suited for analysis using the simulator developed by Davis et al. (2015). In the simulator, every batsman has a baseline state of batting characteristics and these characteristics are modified to provide characteristics p_{iowj} which are applicable to the oth over when w wickets have been taken. We therefore only need to slightly modify the code in order to account for prescribed wicket shift behaviours.

To test the idea of increasing batting aggressiveness, we return to the Bangladesh-India matchup previously discussed, and we alter the batting style of Bangladesh using various wicket shift behaviours. The results are provided in Table 5. Again, the results are based on simulating first innings for both Bangladesh and India, and calculating the difference in runs. We first observe that when the wicket shift behaviour is zero (ordinary batting), the win percentage of 21.3% corroborates with the win percentage in Table 3 under the standard lineup. More importantly, we observe that the numbers in Table 5 coincide with our motivating intuition described in Section 1. In particular, we see that the variability (last column) increases as batting aggressiveness (i.e. wicket shift behaviour) increases. Also, in terms of win percentage, we observe that there is an initial benefit to Bangladesh through increased aggressiveness although the benefit decreases when aggressiveness becomes too great. Additional simulations indicate that the maximum benefit occurs for wicket shift behaviour of -0.9. At this value, the win percentage increases to 22.8% from 21.3% under ordinary batting.

Table 5: Investigation of various wicket shift behaviour (WSB) for Bangladesh based on their their January 17, 2016 lineup in a match versus Zimbabwe. The opposition team is India based on their their January 31, 2016 lineup in a match versus Australia. The table reports win percentage (W%) for Bangladesh, run differential in favour of Bangladesh (RD) and the standard deviation of RD.

WSB	W%	RD	SD(RD)
0	21.3	-22.1	28.6
-1	22.8	-20.9	28.9
-2	22.5	-21.6	29.4
-3	21.2	-23.2	29.7
-4	19.6	-25.2	30.2
-5	17.1	-28.5	30.7

In Table 6, we repeat the analysis except this time we consider New Zealand versus India based on New Zealand's lineup on August 16, 2015 in a match versus South Africa. New Zealand may provide a different perspective than Bangladesh since New Zealand is a strong team. In this matchup, we see the same patterns as with Bangladesh versus India. New Zealand has a 60.2% win percentage under wicket shift behaviour -1.2 which represents an increase from a 59.3% win percentage under ordinary batting behaviour. In this example, because New Zealand is the stronger team (see WSB$=0$), the motivation of Section 1 does not apply directly. Although the variance of run differential increases with increasing aggressiveness (see the last column of Table 6), the maximum win percentage achieved at WSB$=-1.2$ is due to a shift in the distribution of run differential rather than variance inflation.

6. General modified lineups

In this section, we consider the comprehensive strategy of determining an optimal lineup. By lineup, we mean the simultaneous consideration of team selection, batting order and bowling order. This problem was considered in Perera et al. (2016) in the context of maximizing expected run differential. We now consider the problem of maximizing expected win percentage. Optimality is achieved through a stochastic search algorithm over the combinatorial space of lineups where expected win

Table 6: Investigation of various wicket shift behaviour (WSB) for New Zealand based on their their August 16, 2015 lineup in a match versus South Africa. The opposition team is India based on their their January 31, 2016 lineup in a match versus Australia. The table reports win percentage (W%) for New Zealand, run differential in favour of New Zealand (RD) and the standard deviation of RD.

WSB	W%	RD	SD(RD)
0	59.3	6.3	27.3
-1	60.2	7.0	27.5
-2	59.8	6.7	27.9
-3	59.0	6.3	28.0
-4	56.6	4.4	28.3
-5	52.7	1.9	28.8

percentage for a particular lineup is obtained via the match simulator.

For illustration, we again consider India based on their January 31, 2016 lineup. The opposition is New Zealand and their baseline lineup from August 16, 2015 is given in Table 7. Corroborating the results from Table 6, we see that New Zealand wins 59% of the simulated matches between these two teams. However, we now optimise the New Zealand lineup and consider team selection from the 15 players which New Zealand named for the 2016 World Cup. We see that the optimal team selection differs considerably from the August 16, 2015 match where Tom Latham, James Neesham, Nathan McCullum, Adam Milne and Mitchell McClenaghan are replaced by Henry Nicholls, Corey Anderson, Tim Southee, Trent Boult and Mitchell Santner. We also observe that the batting lineups differ, especially in the case of Kane Williamson who moves from the opening partnership to the 6th position and Colin Munro who moves from the 7th position to the opening partnership. We remark that throughout the 2016 World Cup, New Zealand placed Munro in the third batting position which is more in keeping with our optimal batting lineup. However, the takeaway message from Table 7 is that New Zealand improved its winning percentage from 59% to 70% against India by using the optimal lineup. In terms of explanation, there may be a number of contributing factors including new players, a changed batting order and a different bowling emphasis.

7. Discussion

This is an extremely practical paper. We have outlined in simple terms how teams may improve their chances of winning. They may do this through modifying their batting order and by modifying their bowling order. The determination of general optimal lineups as discussed in Section 6 requires the specialised software developed by Perera et al. (2016).

The suggestion of modifying aggressiveness in batsmen is not as easy to achieve as the modification of batting and bowling orders. Asking a batsman to be a little more aggressive needs to be communicated and executed in a careful way. Maybe one way of doing this is to ask a batting partnership to try to achieve a specified run rate in a given over. Batting a little more aggressively is something that would require both training (on the part of the batsman) and quantitative expertise (on the part of the team captain or those providing instruction) to specify the correct run rate.

The big issue for us is a desire to see the sport of cricket begin to adopt analytic methods to

Table 7: Batting orders used in the match simulator for India versus two New Zealand lineups. The number of overs of bowling in the optimal New Zealand lineup is given in parentheses. Summary statistics regarding the simulation are given at the bottom.

India (Jan 31, 2016)	New Zealand (Aug 16, 2015)	New Zealand (optimal)
01. RG Sharma	MJ Guptill	MJ Guptill
02. S Dhawan	KS Williamson	C Munro
03. V Kohli	TWM Latham	H Nicholls
04. SK Raina	GD Elliott	L Ronchi
05. Y Singh	JDS Neesham	CJ Anderson
06. MS Dhoni	L Ronchi	KS Williamson
07. HH Pandya	C Munro	GD Elliott (4)
08. RA Jadeja	NL McCullum	T Southee (4)
09. R Ashwin	AF Milne	T Boult (4)
10. JJ Bumrah	MJ McClenaghan	MJ Santner (4)
11. A Nehra	IS Sodhi	IS Sodhi (4)
	Win Pct = 59%	Win Pct = 70%
	Mean(Run Diff) = 6.3	Mean(Run Diff) = 14.8
	StdErr(Run Diff) = 27.3	StdErr(Run Diff) = 28.9

improve performance. At this stage in time, the sport of cricket appears to lag behind many of the world's major sports.

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