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Simulation of Baseball Gaming by Cooperation and Non-Cooperation Strategies

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Abstract. Baseball is a top strategic collective game that challenges the team manager's decision-making. A classic Nash equilibrium applies for non-cooperative games, while a Kantian equilibrium applies for cooperative ones. We use both Nash equilibrium (NE) and Kantian equilibrium (KE), separate or in combination, for the team selection of strategies during a baseball match: as soon as the selection of strategies by NE or KE carries a team to stay match loosing, a change to KE or NE is introduced. From this variation of selection of strategies the team that is losing tends to close or overcome the score with respect to the team with advantage according to the results from computer simulations. Hence, combining Nash selfish-gaming strategies with Kantian collaboration-gaming strategies, a baseball team performance is strengthened.

Keywords. Baseball strategies, cooperation and non-cooperation, Nash equilibrium, Kantian equilibrium, computer simulations.

1 Introduction

Recently, due to the need for strategic reasoning to play sports games like baseball or American football, the formal modeling of this kind of multi-player sports has grown. The multi-player game modeling is of high complexity, and a strategic analysis of these sports should include a huge amount of parameters for fairly automated decision-making support.

1.1 Baseball Gaming and Simulation

Baseball is a bat-and-ball game played on a diamond shaped field. Each team has nine players and usually a match is nine innings long, but if there is no winner in the ninth inning, additional innings are allowed until the match is won; the team that gets more runs throughout the innings is the winner. Runs are scored by an offensive team's players, after they bat the ball and advance from home plate to first, second, and third base and back to home plate without being given out or strikeout by the defense team. The offensive team's batter should hit the ball thrown by the pitcher away from adversaries distributed in the field [1-3]. A team continues to bat until three outs are made by the defensive team and then the offence/defense roles are switched.

In [4] a theoretical model for lift spinning baseballs, measures of the inertial trajectories of ball surface and the center of mass trajectory are used. In [5] factors that determine the direction of the spin axis of a pitched baseball are analyzed, concluding that the orientation of the hand is significant in determining the direction of the ball spin axis and for increasing the lift force; the palm needs to face home plate. [6] studied contextual influences on baseball ball-strike decisions by umpires, players, and participants, noting that a task as seemingly simple and the objective as judging a baseball pitch is complex and influenced by contextual factors.

The automation of baseball gaming comprises of the basic and compound defense or offence plays by i player [7] and are denoted by the abbreviations in Table 1. Plays are weighted and total ordered regarding their average frequency of occurrence from MLB (Major League Baseball) statistics (see Figure 1), e.g., *strike*(*s*) occurs more

$$s^i \geq b^i \geq f^i \geq co^i \geq o^i \geq p^i \geq ce \geq hi^i \geq a1^i \geq a2^i \geq d^i \geq dp^i \geq a3^i \geq a4^i \geq ca^i \geq r^i \geq fs^i \geq h^i \geq tb^i \geq bp^i \geq bg^i \geq w^i \geq tp^i \geq t^i \geq bo^i$$

Fig. 1. Ordered plays

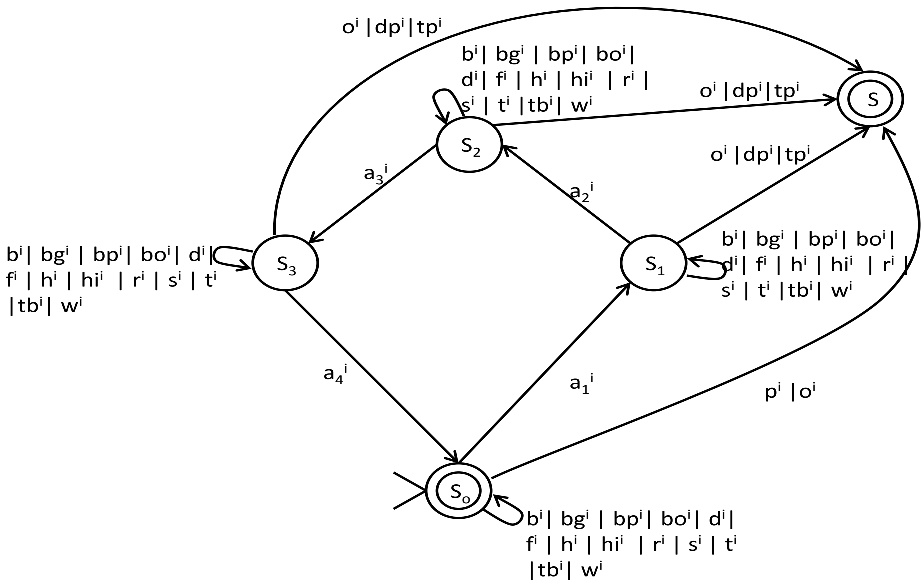


Fig. 2. Baseball FSM diagram

Table 1. ∑ = Terminal symbols to simple plays

Plays descriptions	
b^i: ball	t^i: triple
bo^i: bolk	tb^i: bunt
bg^i: base hit	tp^i: triple play
bp^i: base on balls	w^i: wild pitch
d^i: doublet	wb^i: wait batter´s action
f^i: foul	
dp^i: double play	$a_1{}^i$: move to A_1
fs^i: sacrifice fly	$a_2{}^i$: move to A_2
co^i: contact of ball	$a_3{}^i$: move to A_3
h^i: homerun	$a_4{}^i$: move to home
hi^i: hit	ce: team change
r^i: stealing base	o^i : out
s^i: strike	p^i: punched

frequently than *hit* (*hi)*, being precision weighted from own computer simulation matches.

Formal CFG (context-free grammar) rules set the generation of any simple or complex baseball gaming description, including a whole match. The baseball context-free language is read by the associated push-down automaton (PDA), hence any simple or complex baseball expression is formal correct. The occurrence of plays is in a real-life-like manner such that the higher the frequency of occurrence of a play in real human matches, the higher the probability the play is included in the match formal account and simulation [7]. The PDA for baseball is shape-of-field-like modeled: the home, 1st, 2nd, 3rd bases, and a special base, these bases are modeled as the PDA states; the transitions between the states (one to one) are the plays (movements) the players can perform, (see baseball PDA in Figure 2), also see Appendix A.

There is a generator of baseball plays that produces strings that must have a correct sequence of moves, i.e., baseball plays should be generated according to their average frequency of occurrence in real life matches and the sequence should be consistent with reality. A generator of plays is useful, because it generates valid baseball strings randomly, quickly, and easily. The generator produces baseball plays and verifies that

– These strings must be made based on their average occurrence frequency, and also
– Be generated following the rules of the game.

The generator has a module for generation and validation of strings. Once having a baseball play to perform, that baseball play has to be concatenated with the previous plays. The way to do this is as follows: at the right end of a string, empty one (ε) in the beginning, the play is concatenated with the previous ones and also indicating the player who performs it. CFG, PDA, and the generator of plays are the algorithmic fundament for this automation, which attains similar scores to the human teams' matches in real life.

1.2 Strategy Thinking: Cooperation and Non-Cooperation

Strategies are organized and weighted actions practiced to obtain the maximum available profit up to the minimum effort [8-10]. Regarding the game rules, a player should determine the order and preference of his own actions and strategies joint to the threat embodied in the other players' strategies with the purpose to obtain match success [11-13]. A successful result in matches of collective sports essentially depends on mutual team members cooperation, and non-cooperation may carry to unsuccessful results [14]. Team games highlight positive participation among players as a strategic basis to achieve match success, and a loss of every player's protagonist role is needed for a team's efficient cooperation strategy [15].

The multi-player baseball game is application of the team strategies thoughts obligatory for playing [1]. Baseball is, at the same time, cooperative from a team's perspective and sometimes non-cooperative from a player's perspective: team members are encouraged to aim at best individual actions but must cooperate for the team's best benefit. This tension needs to be solved in the best possible way to avoid frustration from the whole team or from each individual gamer. The strategies to organize the actions are indicated by the team manager regarding each player profile as well as the specific match circumstance aimed to obtain the maximum benefit [16]. A fine strategy should include both the individual and the team motivation.

Nash equilibrium (NE) mathematical model [17] has been a classic in the design of economy models around the world. In Game Theory, NE is the formal fundament of non-cooperative game and commonly used for decision-making in competitive scenarios [12]. The automation of baseball strategic gaming by applying a Nash equilibrium for selection of strategies by a team is performed and the strength obtained has been analyzed in [7]. However, a NE strategy profile is frequently not Pareto optimal and may not lead to the best decision-making for a team but just to a half-good for individuals, which could, in the long term, have negative impact for the whole team. Kantian equilibrium (KE) formalism supports the design of Pareto models in economy and the theoretical optimal team collaboration [18]. KE guarantees that commitment to each other allows the theoretical optimum on team collaboration [18, 19]. For decades Pareto efficiency has been well known to be a benchmark to select, from a population of solutions, the optimal for a problem solution in engineering fields, and, in evolutionary algorithms, to select the next generation of individuals [20].

In this paper, the selection of strategies based on either Kantian equilibrium [18, 19], or on Nash equilibrium, or on both, is analyzed. Kantian equilibrium rules the team cooperation keeping in mind that people's mutual confidence is an assumed condition for a successful team. The abilities of each group member are added in the collective procedure facing a complex task deployment, which allows a theoretical Pareto-efficient design of collective strategies to work up a complex task. However, this theoretical perspective on each member's best strategies, in a real (non-theoretical) match, may not be the times followed. The pass from theory to practice enlightens the usefulness of each of Nash or Kantian equilibriums in a real baseball match. The relevance of use of each of the equilibriums is shown from a set of simulations, which apply either each or both equilibriums at the opportune moment so to strengthen the team performance. Actually, the selection of baseball strategies by combining Nash and Kantian equilibriums results in a superior team performance than by using a single equilibrium according to the computer simulations results.

The rest of the paper is organized as follows. Section 2 presents the algorithms of a baseball match and the selection of strategies. Section 3 describes experiments and the analysis of results of strategy selection by using NE-KE, each by itself and emphatically in combination. Discussion in Section 4 is followed by the Conclusions.

2 Selection of Strategies

The main offensive strategy is the appointment of the batting order at a baseball match start: on first position place quick-footed people, then the best hitters on 3rd and 4th position for a homerun or a good hit. Thus, a player on base could advance more for one run annotation; besides, a runner's advance can be by base stealing, or by applying a sacrifice-plays-based strategy even if it involves an out [21]. On the other hand, the defensive team's purpose is to achieve as many outs as possible, hence not to receive too many pitches and to limit the opposing team's moves.

The NE and KE formal account for multi-player games follow. The joint actions from all the players set the strategy profile vectors; position *i* corresponds to the player i action.

Let $P = \{1, \ldots, n\}$ be a set of players, $i \in P$, $a_x{}^i \in \Sigma^i$ be an element of a set of simple plays, and $s_x{}^i$ be a strategy of player i, $s_x{}^i \in S_i$; let $G = (S_1, \ldots, S_n; u_1, \ldots, u_n)$ be a *game in normal form* [17] where:

- A strategy is a compound sequence $s_x{}^i = a_1{}^i \ldots a_n{}^i$;
- A strategy profile $(s_1, \ldots, s_n)$ is an *n*-tuple of strategies, one strategy per player;
- S_i is a set of strategies of player i;
- $\{S_1, \ldots, S_n\}$ is a set of all the S_i strategies;
- $\{u_1, \ldots, u_n\}$ is a set of all payoff functions one per player;
- $u_i\,(s_1, \ldots, s_n) = r$, where $(s_1, \ldots, s_n) \in S_1 \times \ldots \times S_n$, $r \in \mathbb{R}$.

2.1 Nash Equilibrium for Non-Cooperation Strategies

Nash equilibrium [17] is a widely used mathematical concept in game theory, especially in non-cooperative games. To identify the strategy profiles that satisfy the condition of a Nash equilibrium, every strategy profile is evaluated with the payoff functions of the players, and the chosen profiles are those which for every player are the options that produce less loss for them individually and non-cooperatively, the best options for each player. The mathematical definition is given below.

Each player's NE strategies are denoted $s_1{}^*, \ldots, s_n{}^*$, and $s_i{}^*$ are the non-cooperative answers from i to the $n-1$ other players' strategies. $(s_1{}^*, \ldots, s_i{}^*, \ldots, s_n{}^*)$ is the *n*-tuple of players' strategies that maximizes the payoff function in Equation (1):

$$u_i(\,s_1{}^*, \ldots, \boldsymbol{s_i}{}^*\,, \ldots, s_n{}^*) \geq u_i(\,s_1{}^*, \ldots, \boldsymbol{s_i}\,, \ldots, s_n{}^*)\ \ \forall i \in P, \boldsymbol{s_i}\ \in S_i. \quad (1)$$

Every strategy profile is each payoff function valued and compared with all of the others to determine whether it is or is not dominated. Analysis of each strategy profile follows: a strategy profile x_1 is set for each player i, the strategy profile is modified by altering the player current strategy whilst keeping the strategies of the other $n-1$ players unchanged; if any deviation in the strategy profile evaluated in u_i dominates x_1, i.e., the player i's profit is higher in that deviation profile, then x_1 is a dominated profile and it is discarded. The dominated profiles are discarded and the non-dominated profiles fit the Nash equilibrium (see Table 2). Any game in (finite) normal form has at least one strategy profile that fits the Nash equilibrium [17]. Observe that in NE every player applies a non-cooperative perspective – less bad for him regarding the other players' strategies.

Table 2. Algorithm of Nash equilibrium strategy profile

***Pseudocode* 1:** Input each strategy profile and its payoff value

```
for every sp = (sp1,…,spm) strategy
  profile
  for every player i =1,…,n
    if sp is non-dominated
      Do the deviations in sp for
      player i
      if sp is dominated by at
      least one deviation of i
         labeled sp as dominated;
         move to the next strategy
         profile
      end if
    end if
    else move to the next strategy
    profile
  end for
end for
```

Step 1: For each player, the deviations for each profile are analyzed in order to acquire the non-dominated profiles and discard the others.

Step 2: The non-discarded profiles fit Nash equilibrium.

2.2 Kantian Equilibrium for Cooperation Strategies

In Kantian equilibrium [19] all players have a common strategy space S. In a normal form game $G = (S; u_1, \dots, u_n)$, a strategy profile $L = (s_1, \dots, s_n)$ is Kantian if Equation (2) holds:

$$u_i\,(L) \geq u_i\,(\alpha L)\ \ \forall\ i \in P,\ \alpha \in \mathbb{R}_+. \qquad (2)$$

All of the player action values are weighted by the same factor α. This is community cooperation in theoretically equal conditions and no player takes advantage of any other. By KE usage every player applies the Pareto efficient best own strategy from a cooperative perspective, and there is at least one strategy profile for a game in normal form that fits Kantian equilibrium, as for NE. For KE, all players get the maximum profit; in fact, a player changes his strategy if and only if each player changes its strategy by the same multiplicative factor α (see the algorithm in Table 3).

Table 3. Algorithm of Kantian equilibrium strategy profile

***Pseudocode* 2:** Input each strategy profile and its payoff value

```
for every sp =
  (sp1,…,spm)strategy profiles
    for every player i =1,…,n
        benefit-degree^sp
        +=sp.profit
    end for
end for
find the highest benefit-
  value(s)
```

Step 1: For each profile, the benefit value is the sum of all the players' profits in this profile.

Step 2: From the benefit values determine the highest one.

Step 3: Every profile with the highest value fits Kantian equilibrium.

For each of NE and KE and each team and/or player, a set of payoff matrices comprise the quantitative analysis by regarding: 1) if the match is at the first, middle, or late innings, 2) the score conditions (winning, losing, or drawing), 3) the number of outs in the inning, and 4) the players' position on the bases following the methodology in [7].

Next, payoff-matrices comprise the payoff function valuations of the strategy profiles. Each matrix entry arranges each player strategy profile valuation. The M payoff matrix for n players is arranged from the set of M^i payoff matrix of every player i. The M entries are the strategy profiles joint to the profile payoff value r_z, hence $((s_1, \dots, s_i, \dots, s_n), r_z)$. The payoff matrices data can support the manager's decision-making in the course of a match. The payoff matrix comprises the quantitative analysis for a whole baseball match based on the combinations from first, middle, and late innings, three score conditions, the number of outs, and eight players' position on base. One

	Matrix p_1		Matrix p_2		Matrix p_3	
1	(*h*, *r*, *r*)	0.3	(*h*, *r*, *r*)	0.2	(*h*, *r*, *r*)	0.0
2	(*h*, *r*, *wb*)	0.3	(*h*, *r*, *wb*)	0.2	(*h*, *r*, *wb*)	0.1
3	(*h*, *wb*, *r*)	0.3	(*h*, *wb*, *r*)	0.2	(*h*, *wb*, *r*)	0.0
4	(*h*, *wb*, *wb*)	0.3	(*h*, *wb*, *wb*)	0.2	(*h*, *wb*, *wb*)	0.2
5	(*hr*, *r*, *r*)	0.5	(*hr*, *r*, *r*)	0.2	(*hr*, *r*, *r*)	0.1
6	(*hr*, *r*, *wb*)	0.2	(*hr*, *r*, *wb*)	0.2	(*hr*, *r*, *wb*)	0.2
7	(*hr*, *wb*, *r*)	0.2	(*hr*, *wb*, *r*)	0.2	(*hr*, *wb*, *r*)	0.2
8	(*hr*, *wb*, *wb*)	0.2	(*hr*, *wb*, *wb*)	0.2	(*hr*, *wb*, *wb*)	0.2

Fig. 3. Payoff matrices for p_1, p_2, and p_3

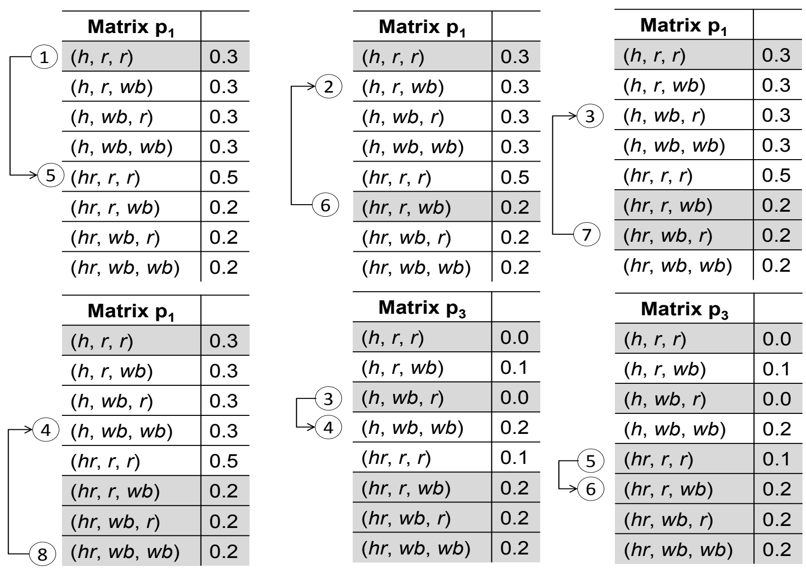


Fig. 4. Deviations in the strategy profiles

matrix per each analysis based on NE or KE is constructed.

2.3 Computational Complexity

The proposed algorithms for baseball match analysis make deviations of profiles to rule out those profiles that are dominated for all players. The Nash profiles are non-dominated, and for the case of Kantian equilibrium they are those where the players get the maximum profit. The computational complexity is k^n, with k being the number of strategy profiles and n being the number of players in the worst case. Actually, by analyzing the Nash equilibrium algorithm, the strategy profiles dominated by one player are no longer analyzed by the successive players.

2.4 Examples

An example of NE or KE being applied to identify the strategy profiles that fit each in a match gaming follows. Let the player p_2 be at third base, one out in the last inning, and the match score tied. One p_2 option is to try to *steal the base* (*r*), or wait for the action of player at bat (*wb*). For the player p_1 at bat positions an option is to try to make a *homerun* (*h*), or try to make a *sacrifice fly* (*fs*). In Table 4 we show the players' profit for each profile. The NE profiles are (*h*, *r*) and (*fs*, *wb*), and the KE profile is

Table 4. Payoff matrices to analyze NE or KE profiles for p_1 and p_2

		p_2	
		hr	*fs*
p_1	*r*	(0.3,0.3)	(0.2,0.1)
	wb	(0.1,0.2)	(0.2,0.2)

(*h*, *r*). NE profile (*h*, *r*) and (*fs*, *wb*) are found by considering the profile (*fs*, *r*): if p_1 changes his strategy to *h*, he obtains higher profit, so (*fs*, *r*) profile is dominated and discarded. Using (*h*, *wb*) profile if p_2 changes his strategy to *r*, he obtains higher profit also, so (*hr*, *wb*) profile is discarded. Using (*fs*, *wb*) or (*h*, *r*) profiles, no player gets higher profit changing his strategy, so these profiles are not dominated NE profiles. Profile (*h*, *r*) fits KE because both players get the highest profit.

Complex examples for identifying Nash or Kantian equilibrium in some baseball gaming using the matrix representation previously explained are introduced. Let p_1, p_2 and p_3 be the players; p_1 is at home-bat position and can make a hit (*hi*) or a home run (*h*), while p_2 is at 2nd base, and p_3 is at 1st base; p_2 and p_3 have the same options – *steal the base* (*r*), or wait for the action of p_1 at bat (*wb*) (see the payoff matrices of each player in Figure 3).

How the NE profiles are found by identifying the dominated and non-dominated profiles, when the player changes his strategy up to the other players' strategies is shown in Figure 4. Fix a player, x/y means that profile x dominates profile y, so for player p_1 we have 5/1, 2/6, 3/7, and 4/8**;** for player p_3 domination is by 4/3, 6/5; and for player p_2 there are no dominated profiles. Therefore, the non-dominated profiles for all players are the profile 2, (*hi*, *r*, *wb*) and the profile 4, (*hi*, *wb*, *wb*), and both fit the NE condition. The only KE profile is (*h*, *r*, *r*) because in this case the players' profits are maximum as a team.

3 Experiments on Merge Selection of Strategies

Experiments concern the performance comparison of teams that use a method for selection of strategies with regard to the next match gaming conditions:

– Comparing the MLB results from some teams against the simulation results by applying Nash equilibrium or Kantian equilibrium;

Table 5. Some MLB baseball players' statistics

Player	T	AB	H	2B	3B	HR	BB	SO	SB	CS
Suzuki, I	NYY	227	73	13	1	5	5	21	14	5
Jeter, D	NYY	683	216	32	0	15	45	90	9	4
Cano, R	NYY	527	196	48	1	33	61	96	3	2
Nunez, E	NYY	89	26	4	1	1	6	12	11	2
Chavez, E	NYY	278	78	12	0	16	30	59	0	0
Swisher, N	NYY	537	146	36	0	24	77	141	2	3
Cespedes, Y	OAK	487	142	25	5	23	43	102	16	4
Moss, B	OAK	265	77	18	0	21	26	90	1	1
Gomes, J	OAK	279	73	10	0	18	44	104	3	1
Crisp, C	OAK	455	118	25	7	11	45	64	39	4
Reddick, J	OAK	611	148	29	5	32	55	151	11	1
Smith, S	OAK	383	92	23	2	14	50	98	2	2

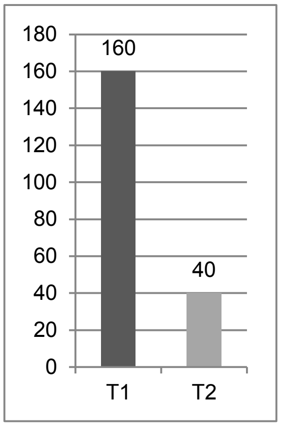


Fig. 5. T_1 NE vs. T_2 NYY

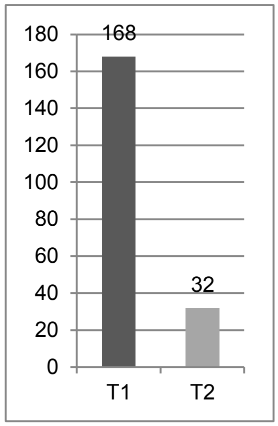


Fig. 6. T_1 NE vs. T_2 OAK

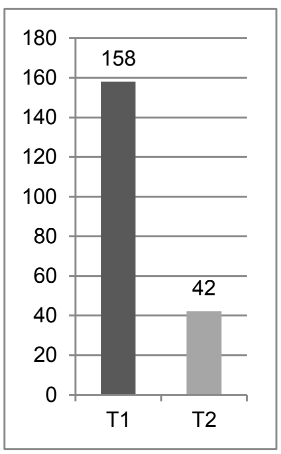


Fig. 7. T_1 KE vs. T_2 NYY

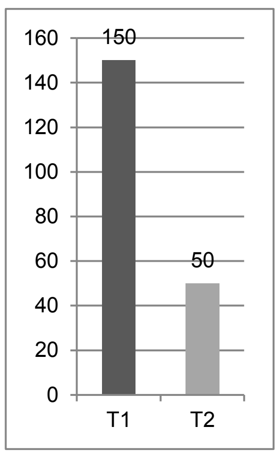


Fig. 8. T_1 KE vs. T_2 OAK

- A team with a score disadvantage changes from Nash equilibrium to Kantian equilibrium (NE-KE), and vice-versa (KE-NE);
- Using Kantian equilibrium by a defense team for exclusive, versus Nash equilibrium use by offensive teams for exclusive.

3.1 Simulations Using MLB Data and Selection of Strategies

To simulate the players' actions according to their performance, we use MLB real statistics from the New York Yankees (NYY) and Oakland Athletics (OAK) in the 2012 season (some data are in Table 5). Shown is the number of times that a player

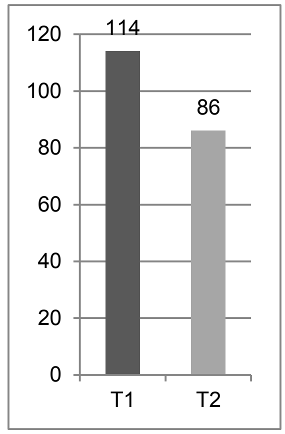


Fig. 9. T_1 vs. T_2 item (1)

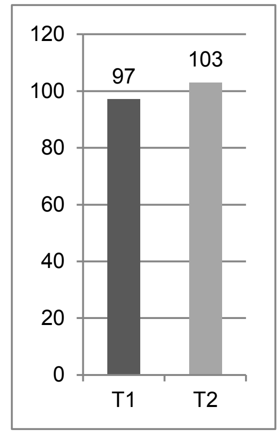


Fig. 10. T_1 vs. T_2 item (2)

makes **AB** at bat, **R** for reach home base, **H** for a hit, **2B** for a hit and reaches second base, **3B** for a hit and reach third base, **HR** for a home run, **BB** for walk by a player (four balls during at bat), **SO** for strikeout (three strakes during at bat), **SB** for stolen a base, **CS** for a player put out by attempting to steal a base.

Using the MLB statistics [22], the frequency of occurrence of each baseball play per player is used to induce the probability the play can happen in a match, e.g., the probability of a player making a hit is given by **AB**/**H**, a home run by **AB**/**HR**, and so on. Thus, when a player is at bat, we can simulate his performance in a gaming (e.g., 2012) season. Next, we make a comparison among simulations of baseball matches using MLB statistics, without any concern for analysis of strategies, versus simulations that use NE or KE as the methods for selection of strategies. Two hundred computer simulations per each of the following conditions were carried out:

1. Team 1 (T_1) uses NE versus Team 2 (T_2) uses NYY MLB statistics;
2. T_1 uses NE versus T_2 uses OAK MLB statistics;
3. T_1 uses KE versus T_2 uses NYY MLB statistics;
4. T_1 uses KE versus T_2 uses OAK MLB statistics.

By considering the results in Figure 5, when T_1 uses NE and T_2 uses NYY statistics, T_1 is 160/40 superior. The results in Figure 6 show when T_1 uses NE and T_2 uses OAK statistics, and T_1 is 168/32 superior. The results in Figure 7 show when

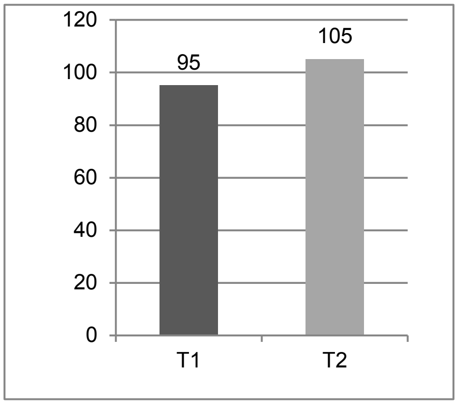


Fig. 11. T_1 vs. T_2 item (3)

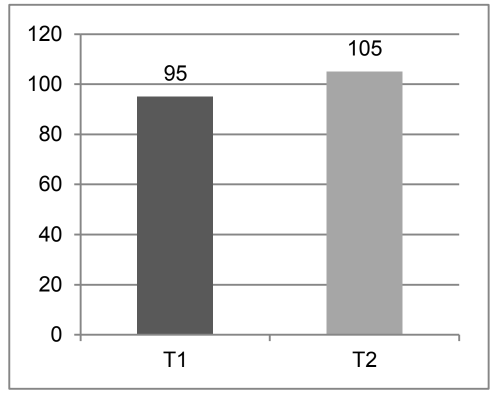


Fig. 12. T_1 vs. T_2 item (4)

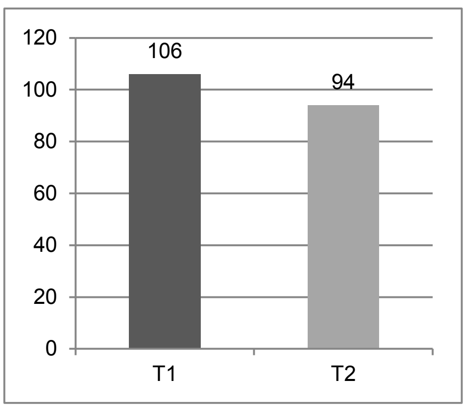


Fig. 13. T_1 vs. T_2 item (5)

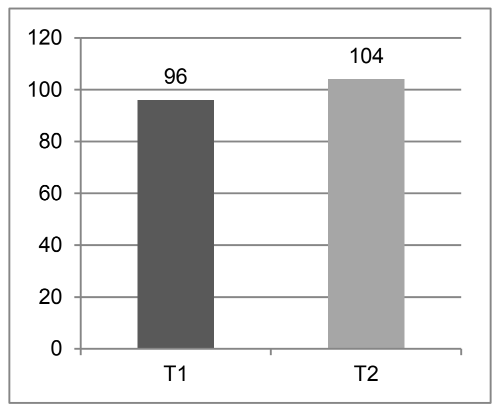


Fig. 14. T_1 vs. T_2 item (6)

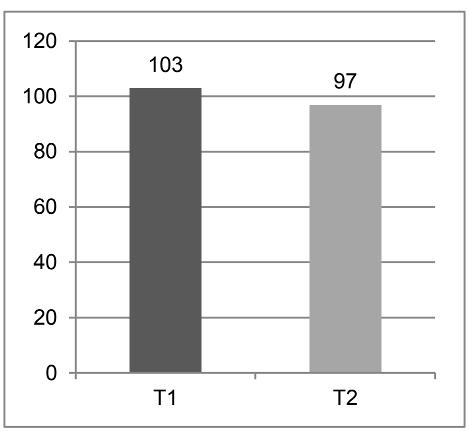


Fig. 15. T_1 vs. T_2 item (7)

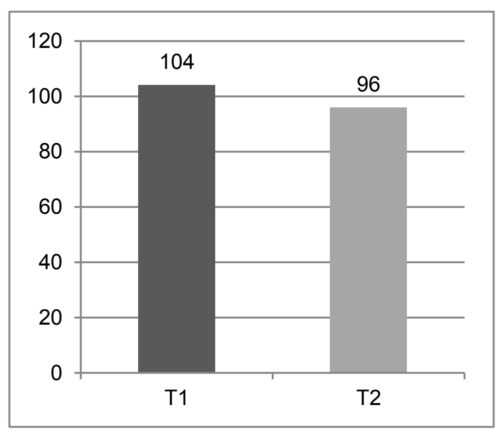


Fig. 16. T_1 vs. T_2 item (8)

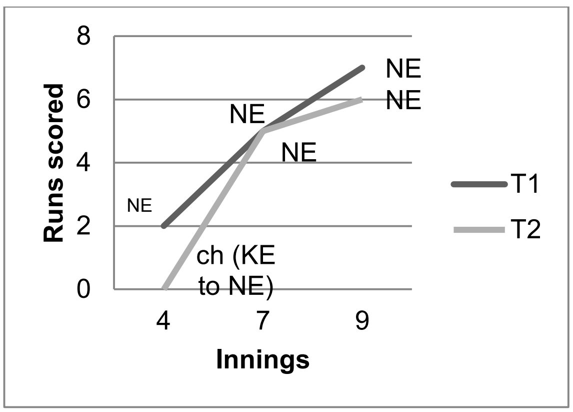
T_1 uses KE and T_2 uses NYY statistics, and 158/42 wins in favor of T_1. The results in Figure 8 illustrate when T_1 uses KE and T_2 uses OAK statistics, and T_1 won more times 150/50.

A huge contrast between the results from the previous simulations quantifies the relevance of the selection of strategies, even for a team having top level baseball players, whose inclusion does not guarantee a high level team performance. Therefore, analysis of methods for guiding players' actions as a team is primordial for selection of proper strategies to increase the probability of team success in a match.

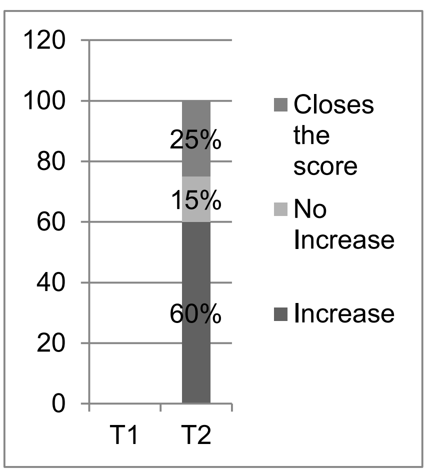
3.2 Combining Nash and Kantian Equilibrium

Two hundred simulations per each of the following selection of strategies, sometimes combinations of them, were carried out:

1. T_1 uses NE and T_2 uses KE;
2. T_1 uses KE and T_2 uses NE;
3. T_1 starts using NE and T_2 starts using KE, then change to KE or NE, respectively;
4. T_1 starts using KE and T_2 starts using NE, then change to NE or KE, respectively;
5. T_1 uses NE always and T_2 uses combination of KE-NE;

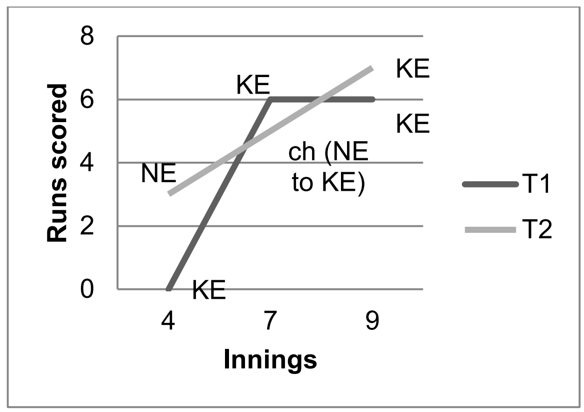


(A)

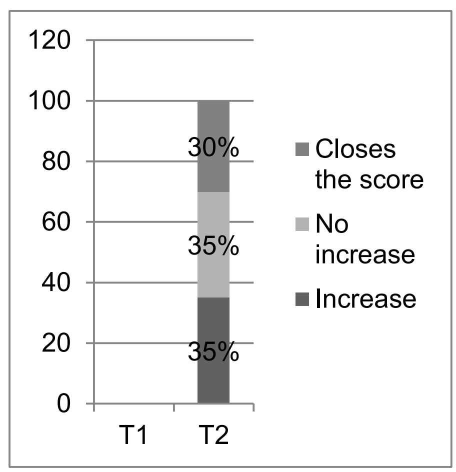


(B)

Fig. 19. Analysis of team strategy technique change, item (5)



(A)



(B)

Fig. 20. Analysis of team strategy technique change, item (6)

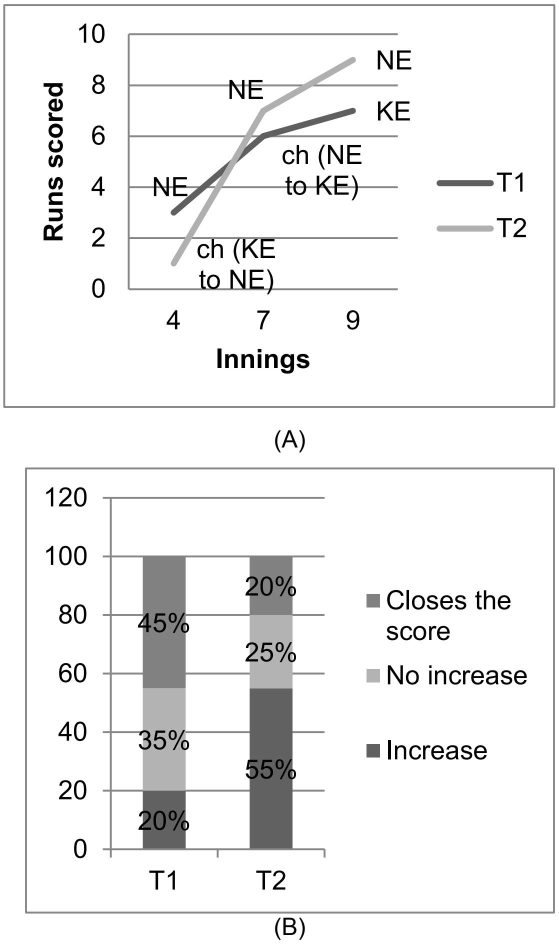


Fig. 17. Analysis of team strategy technique change, item (3)

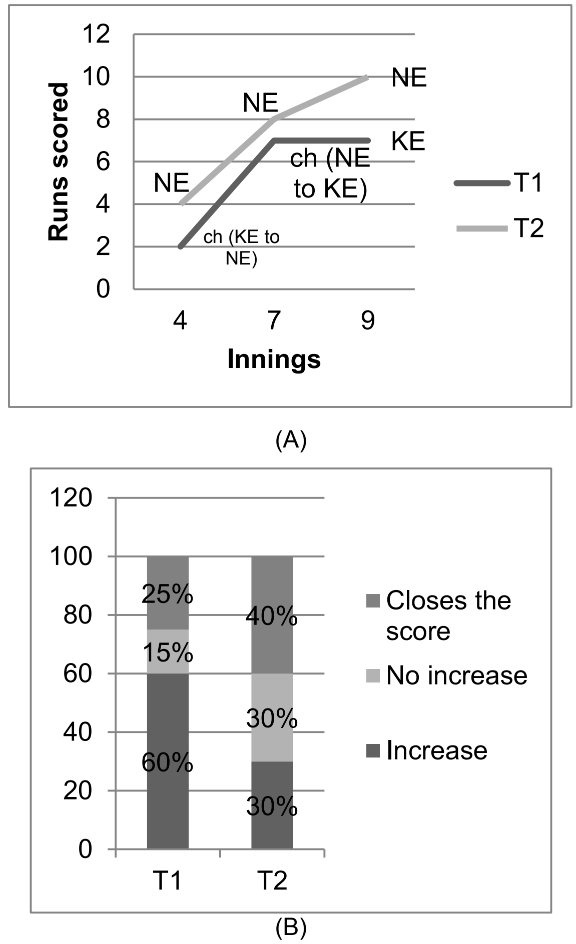


Fig. 18. Analysis of team strategy technique change, item (4)

6. T_1 uses KE always and T_2 uses NE-KE;
7. T_1 uses combination of KE-NE and T_2 uses NE always;
8. T_1 uses combination of NE-KE and T_2 uses NE always.

Observe that a change of selection of strategies occurs at the first middle inning 4th or at the first late inning 7th, and if needed at extra 9th inning. Considering the results in Figures 9-10, items (1-2), the team that uses NE for selection of strategies in baseball gaming, either for defense or the offensive role, has advantage over the team that uses KE. In Figures 11-12, items (3-4), when a team, as soon as it is losing, changes its strategy from NE to KE, or vice versa, the results illustrate that the change is beneficial to the team because the score is closing, and sometimes the team that is losing can overcome the score. Figures 13-16, items (5-8), show the results when one team fixes the strategy analysis and the other changes, and this last obtained an advance.

3.3 Changes of Strategy

Next, our analysis focuses on the case when T_1 and T_2 change their strategy selection method for items (3-8). In Figure 17 the result shows the case when T_1 begins NE and T_2, KE. Both change selection of strategies method NE-KE or KE-NE

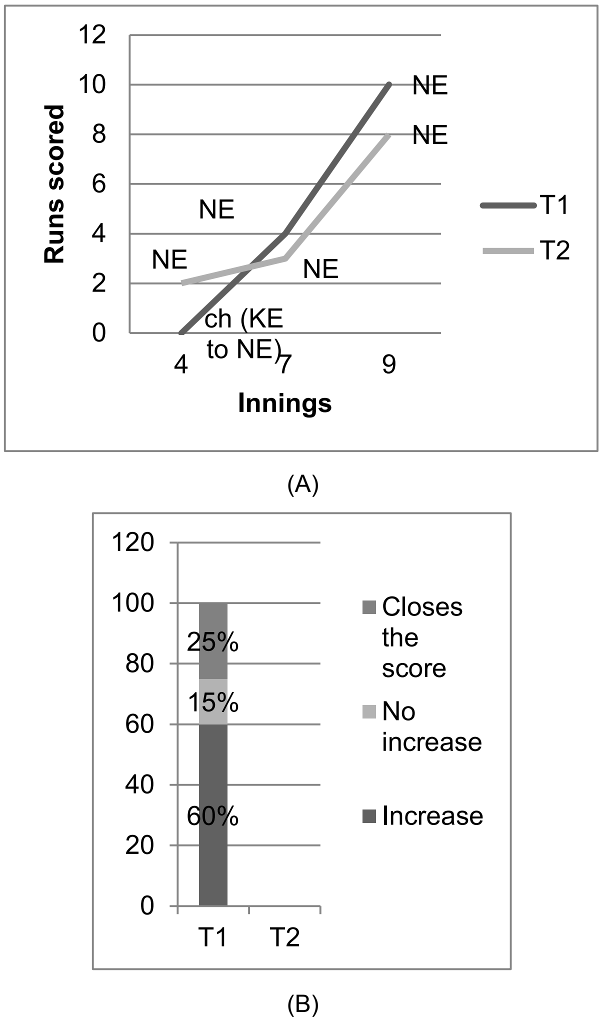


Fig. 21. Analysis of team strategy technique change, item (7)

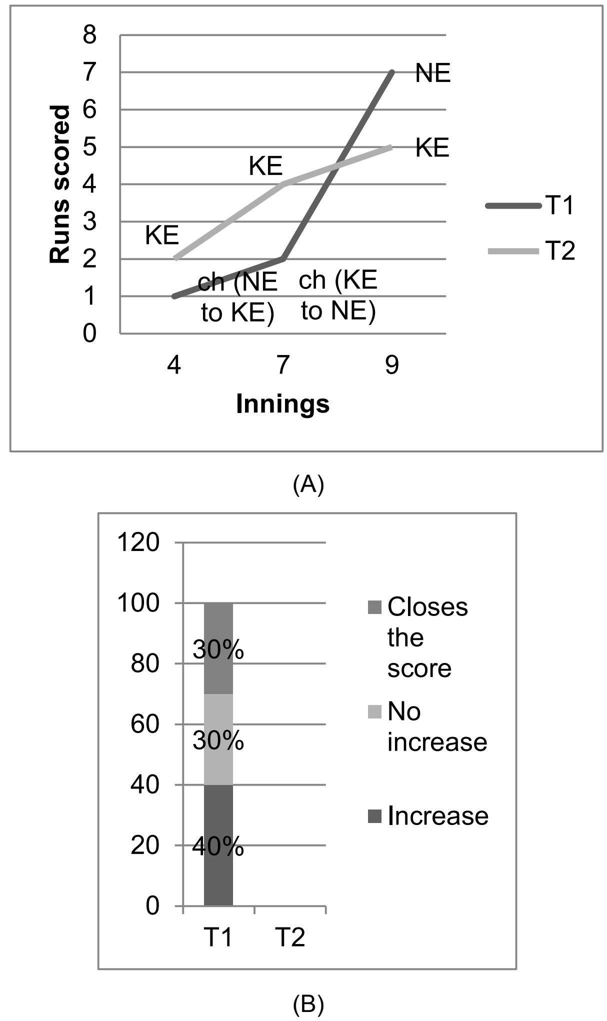


Fig. 22. Analysis of team strategy technique change, item (8)

when losing. In Figure 17 (A) T_2 changes KE-NE in the 4th inning and the score increased; in the 7th inning the T_1 changes NE-KE maintaining the score. Figure 17 (B) shows the percentage of increase, no increase, and score closeness when teams change the selection of strategies. For T_1 the 20% increased, 35% did not increase, and 45% closed the score when it changed NE-KE. Furthermore, for T_2 the 55% increased, 25% did not increase, and 25% closed the score when it changed KE-NE. Observe that in some cases both teams change more than once.

Figure 18 illustrates the case when T_1 begins KE and T_2, NE, then both change strategy. In Figure 18 (A) T_1 changes KE-NE in the 4th inning and the score is improved; in the 7th inning T_1 changes NE-KE and the score is unimproved. Figure 18 (B) shows the percentage of increase, no increase, and score closing when team change selection of strategies method: for T_1 60% increased, 15% did not increase, and 25% score closing when there was change KE-NE; for T_2, moreover, 30% increased, 30% did not increase, and 40% closed the score when changed NE-KE.

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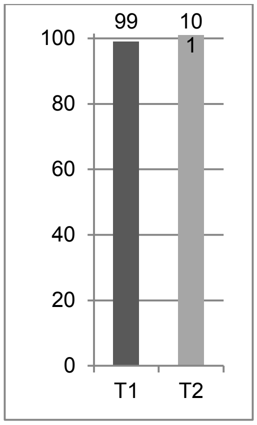

Fig. 23. T_1 vs. T_2 item (1)

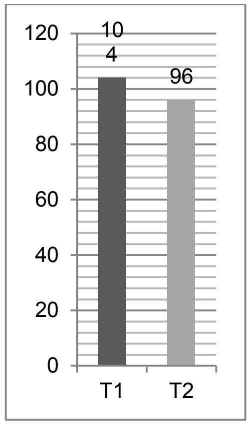

Fig. 24. T_1 vs. T_2 item (2)

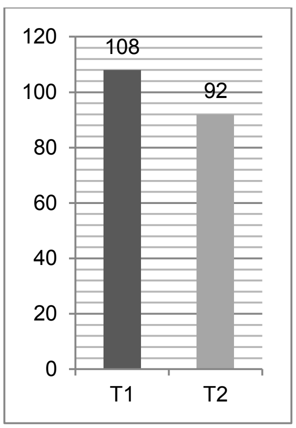

Fig. 25. T_1 vs. T_2 item (3)

In Figure 20 T_1 fixes to KE and T_2 begins NE and can change selection of strategies. In Figure 20 (A) T_2 changes NE-KE in the 7th inning and it did not improve the score. Figure 20 (B) shows the percentage of increase, no increase and score closing when team changes selection of strategies method: for T_2 35% increased, 35% did not increase and 35% score closing by change.

In Figure 22 T_2 fixes KE and T_1 begins NE and can change selection of strategies method. In Figure 22 (A) T_1 changes NE-KE in the 4th inning, and does not improve the score, T_1 changes NE-KE in the 7th inning improving his score. Figure 22 (B) shows percentage of increase, no increase, and score closing when team changes selection of strategies method; for T_1 40% increased, 30% did not increase, and 30% score closing when selection of strategies method was changed.

The results obtained revealed the positive impact, the percentage of gain or loss, the change of strategy selection for a team regarding items (3-8); thus the advantage of using NE or KE for strategy selection in a baseball match.

3.4 Offensive versus Defensive Strategies

Now, we analyze the impact of NE for the offensive role and KE for the defensive role, to observe whether NE/KE is well behaved for the specific defensive/offensive role, versus the usage of NE or KE during the whole match without any change. Two hundred simulations of baseball matches per each of the following items were performed (see results in Figures 23-25):

1. Both T_1 and T_2 use NE for offensive role and KE for defensive role;
2. T_1 uses NE for offensive role and KE for defensive role, and T_2 only uses NE;
3. T_1 uses NE for offensive role and KE for defensive role, and T_2 only uses KE.

From the results illustrated in Figures 23-25, it may be concluded that the teams using NE for the offensive role and KE for the defensive role achieve better performance than those that only use one method for selection of strategies gaming any of the roles.

The percentage of strategy profiles being likewise KE and NE is 58%. The remaining 42% is of different strategy profiles. In addition, when the analysis determines that NE strategic profiles should be done for gaming, the percentage of really practiced ones is 71%, whereas for KE, 46% is practiced.

4 Discussion

In Game Theory a formal account of a game models the adversaries' alternate plays to determine the course of actions and strategies of each player and the whole team during the match [23]. The game rules should be unambiguously determined to hold the analysis on competition; the benefit to apply the selected actions and strategies

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is evaluated by means of mathematical payoff function [24-26].

In the real circumstance of a baseball match, sometimes the sacrifice play occurrences fit a NE strategy profile that is beneficial for the team; e.g., the batter is able to support a run by applying a sacrifice hit, so a teammate can advance to home; another way to achieve the run is a batter's homerun. Sacrifice-hit is a more likely combination than homerun. The first option is Nash equilibrium, while the second is Kantian equilibrium. An experienced manager (and team), by regarding tied match circumstances, chooses more likely options in real life matches, even they are not theoretical optimal, whose real occurrence is less likely. A baseball match is not a closed and wholly controlled process, but diverse and uncertain nature eventualities may alter the manager's decision, regardless of whether it is based on a formal analysis or on his former experience. In spite of the fact NE is not Pareto optimal, the team performance is better by applying NE than by using KE. Also, the usage of a combination of NE for the offensive role and KE for the defensive role shows better results than the usage of only NE or KE for both roles, respectively. Additionally, a benefit can be seen when a team changes selection of strategies NE-KE or vice versa.

In Section 3.3, we presented a set of experiments concerning the changes of selection of strategies, from Nash to Kantian or vice versa. The computational cost of this change is not substantial, but the change makes a significant improvement on team performance. The computational cost of a strategic choice method is presented in Section 2.2.

5 Conclusions

In this paper, we use a combination of non-cooperative Nash equilibrium and cooperative Kantian equilibrium for the manager's decision-making during a baseball match. The manager's decisions are fundamental in the gameplay, hence, the decisions based on analytical strategic choice methods based on Nash and/or Kantian equilibrium strengthen team performance, thereby increasing the expectations of winning. From a set of computer simulations, the relevance of each of

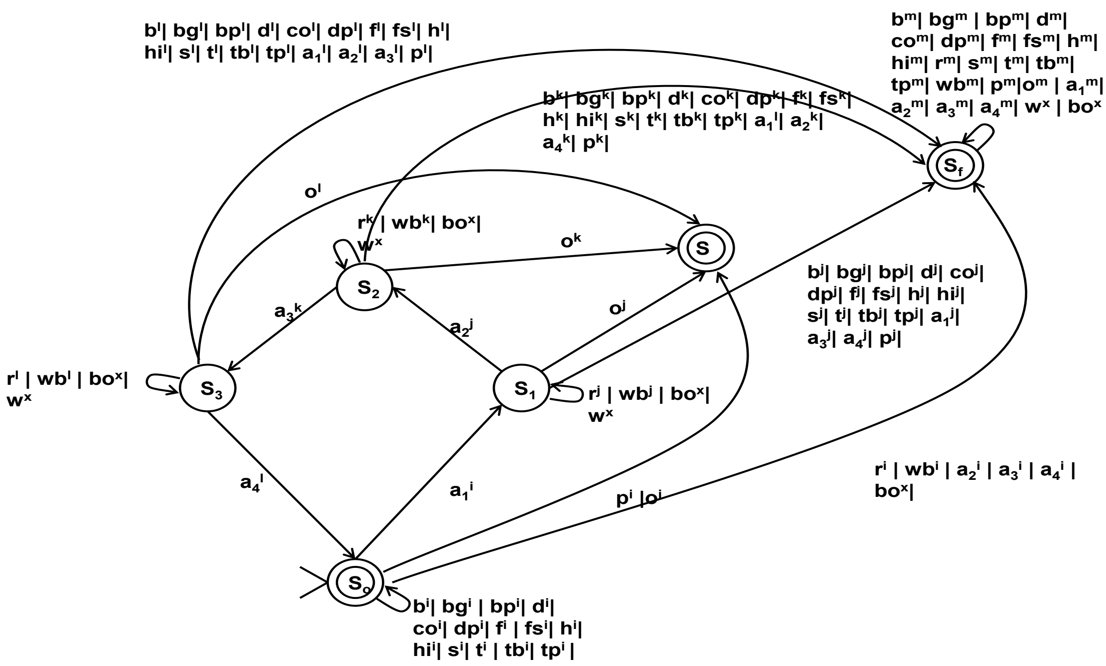

Fig. A.1. Deterministic baseball FSM the equilibriums or both, at the opportune moment, is shown, which strengthens team performance. Mix gaming of Nash selfish-player strategy with Kantian team-cooperation empowers the collective gaming when the team is losing, so it closes or even overcomes the match score with respect to the adversary team. Actually, the tension of selfish intentions versus cooperation, being well handled and applied during a match, strengthens the abilities of the team and the individuals.

Appendix A

Here we present a deterministic FSM for baseball gaming (see Figure A.1). The FSM presented in Figure 2 is non-deterministic, since in some states there are no transitions defined for every element of the alphabet; but for the smart modeling of baseball gaming, this FSA works since it is able to recognize any string of the language generated by the baseball formal grammar. The deterministic FSM that covers all the transitions given any state and any element from the alphabet is as follows (see Figure A.1).

Let $(\Sigma, \hat{S}, s_0, \varphi, H)$ be a deterministic baseball FSM such that

– Σ is the alphabet, see Table 1;

– $\hat{S} = \{s, s_0, s_1, s_2, s_3, s_f\}$ is a set of states;

– $\varphi: \hat{S} \times \Sigma \rightarrow \hat{S}$ is the transitions function;

– $s_0 \in \hat{S}$ is the initial state;

– $H = \{s, s_0, s_f\} \subseteq \hat{S}$ is a set of halt states.

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