Article

Connecting game theory and evolutionary network control for the computational control of soccer matches

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Abstract
Game theory, also known as interactive decision theory, is an umbrella term for the logical side of decision science, including both human and non-human events. In this paper a new game theory model is introduced in order to tame complex human events like soccer matches. *Soccer-Decoder* is a math algorithm recently introduced in order to simulate soccer matches by merging together 3 scientific methods: game theory, differential calculus and stochastic simulations. The philosophy behind *Soccer-Decoder* is that even very complex real world events, when turned into their irreducible essence, can be understood and predicted. In this work, *Soccer-Decoder* is combined with Evolutionary Network Control in order to provide a proficient tool to decide the most proper game strategies for determining winning strategies in soccer events. An illustrative example is given. The ratio behind this work is that even very complex real world events can be simulated and then controlled when using appropriate scientific tools.

Keywords complexity; game theory; Evolutionary Network Control; iteration; real life simulations; soccer event; stochasticity.

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1 Introduction

"Soccer decoding" is a definition introduced by Ferrarini (Ferrarini, 2014) to indicate the use of scientific tools on top of: a) reducing the complexity of a soccer match to its irreducible essence using a game theory (Brandenburger, 2014; Maynard Smith, 1982) algorithm, b) simulating soccer matches by adding iteration and stochasticity to such structural essence.

Soccer-Decoder (Ferrarini, 2012a; Ferrarini, 2014) is a math algorithm, implemented through the software *Soccer-Lab* (Ferrarini, 2012b; Ferrarini, 2014), that simulates soccer matches by merging together 3 scientific methods: game theory, differential calculus and stochastic simulations. The philosophy behind *Soccer-Decoder* is that even very complex real world events, when turned into their irreducible essence, can be understood and predicted.

In this work, *Soccer-Decoder* is combined with Evolutionary Network Control (Ferrarini, 2011a; Ferrarini A., 2011b; Ferrarini, 2013a; Ferrarini, 2013b; Ferrarini, 2013c; Ferrarini, 2013d; Ferrarini, 2013e; Ferrarini, 2014b; Ferrarini, 2015a; Ferrarini, 2015b) in order to provide a proficient tool to decide the most proper game strategies for determining winning strategies in soccer events. The ratio behind this work is that even very complex real world events can be simulated and then controlled using appropriate scientific tools. An illustrative example is given.

2 The *Soccer-Decoder* Algorithm

The math algorithm *Soccer-Decoder* makes use of the following variables and parameters:

- defensive skill (*DS*)
- midfield skill (*MS*)
- offensive skill (*OS*)
- goalkeeper skill (GS)
- field factor (*FF*)
- trainer skill (*TS*)
- players experience (*PE*)
- athletic decay (*AD*)
- game style (*GS*)

Midfield skill is calculated as

$$MS = \sum_k M_k \qquad (1)$$

where M_k is the skill of each midfielder. The number of midfielders is set-up by the user.
Defensive skill is calculated as follows

$$DS = \sum_i D_i + \frac{1}{2}\sum_k M_k \qquad (2)$$

where D_i is the skill of each defender, while M_k is the skill of each midfielder. The rationale is that the defensive phase is made by defenders above all, but also midfielders give a lesser contribution.
The number of defenders is set-up by the user.
Offensive skill is given by

$$OS = \sum_j S_j + \frac{1}{2}\sum_k M_k \qquad (3)$$

where S_j is the skill of each striker, while M_k is the skill of each midfielder. The rationale is that the offensive phase is made by strikers above all, but also midfielders give a lesser contribution. The number of strikers is decided by the user.

The field factor (*FF*), the trainer skill (*TS*) and the players experience (*PE*) add scores to *DS*, *MS* and *OS*. The athletic decay *AD* during the match acts as follows:

$$\begin{cases} \dfrac{dDS}{dt} = -AD * DS \\ \dfrac{dMS}{dt} = -AD * MS \\ \dfrac{dOS}{dt} = -AD * OS \end{cases} \quad (4)$$

Two game styles (*GS)* are possible in *Soccer-Decoder*: ball possession (*BP*) and counter-attack (*CA*). For example, a *BP* action of team 1 happens using the following algorithm:

MS of team 1 VS *MS* of team 2
if *MS* of team 2 wins the battle, then the action of team 1 is over
else
OS of team 1 VS *DS* of team 2
if *DS* of team 2 wins the battle, then the action of team 1 is over (5)
else
OS of team 1 VS *GS* of team 2
if *GS* of team 2 wins the battle, then the action of team 1 is over
else GOAL

In order to decide the winner of each single battle (e.g. MS_1 *vs.* MS_2 or OS_1 vs. DS_2), *Soccer-Decoder* makes use of the following algorithm. Let's suppose that we want to simulate, for a single action, the battle between *OS* of team 1 and *DS* of team 2. *Soccer-Decoder* produces a random number R_1 between 0 and OS_1. R_1 is sampled from a statistical Erlang's distribution

$$\begin{cases} f(x) = \dfrac{1}{\beta(m-1)!}\left(\dfrac{x}{\beta}\right)^{\alpha-1} e^{-x/\beta} \\ \text{with:} \\ m > 0 \\ \beta > 0 \end{cases} \quad (6)$$

with peak exactly equal to *OS*. In other words, the random number R_1 has higher chance to be close to *OS* but it can also, with lower probability, bear values < *OS*.

Then, *Soccer-Decoder* does the same for team 2 and a battle happens where the higher score wins:

if R_1 Є [0, OS_1] > R_2 Є [0, DS_2] then the action continues
else (7)
the action of team 1 is over

Both OS_1 and DS_2 change continuously over time based on eq. (4). This assures a realistic dynamical evolution of the soccer match, where players have an athletic decay that, step-by-step, lowers their performances.

In practice, *Soccer-Decoder* is a math algorithm that iteratively produces game theory battles with dynamical and stochastic parameters. In order to do this, *Soccer-Decoder* merges together game theory with differential equations and stochastic simulations.

Soccer-Lab can simulate one match, but also N matches (e.g., N = 1,000,000). The simulation of N matches obeys the following pseudo-code:

```
FOR matches = 1 TO N
    FOR actions=1 TO 100
        FOR teams=1 TO 2
            APPLY the Soccer-Decoder algorithm          (8)
        NEXT teams
    NEXT actions
NEXT matches
```

For each team, 100 actions are simulated during each single match, since 100 is a common number of actions in recent soccer matches. By the way, the user can define a different number of actions.

3 Evolutionary Network Control

Soccer-Decoder is joined here with Evolutionary Network Control (ENC from now on; Ferrarini, 2011a; Ferrarini, A., 2011b; Ferrarini,2013a; Ferrarini, 2013b; Ferrarini, 2013c; Ferrarini, 2013d; Ferrarini, 2013e; Ferrarini, 2014b; Ferrarini, 2015a; Ferrarini, 2015b).

Such improvement has been thought for two purposes:

1) given a real soccer match, ENC can estimate a set of optimized parameters for *Soccer-Decoder* in order to fit the simulated match to the real one;
2) ENC can find the optimized parameters for a soccer team in order to change a probable defeat into a probable victory (e.g. changing the number of defenders or midfielders or strikers, passing from ball possession to counter-attack and vice versa etc…).

Evolutionary Network Control is a theoretical and methodological framework aimed at the control of ecological and biological networks by coupling network dynamics and evolutionary modelling. ENC covers several topics of network control, for instance a) the global control from inside and b) from outside, c) the local (step-by-step) control, and the computation of: d) control success, e) feasibility, and f) degree of uncertainty. ENC has proven to be effective for both linear and nonlinear networks, either based on differential or difference (recurrent) equations.

Soccer-Decoder plays a soccer match like a network of game theory battles. Such network can be optimized at the beginning of the match (exogenous control) or at each single battle (endogenous control). The first option (Fig. 1) requires that ENC controls only once for all the parameters of the team that is thought to be the winner. For instance, team strategy (3-5-2, 4-4-2, 4-3-3, 3-4-3 etc.) and game style (ball possession or counter-attack) can be optimized once for all at the beginning of the match. The application of ENC to *Soccer-Decoder* has been realized within *Soccer-Lab*.

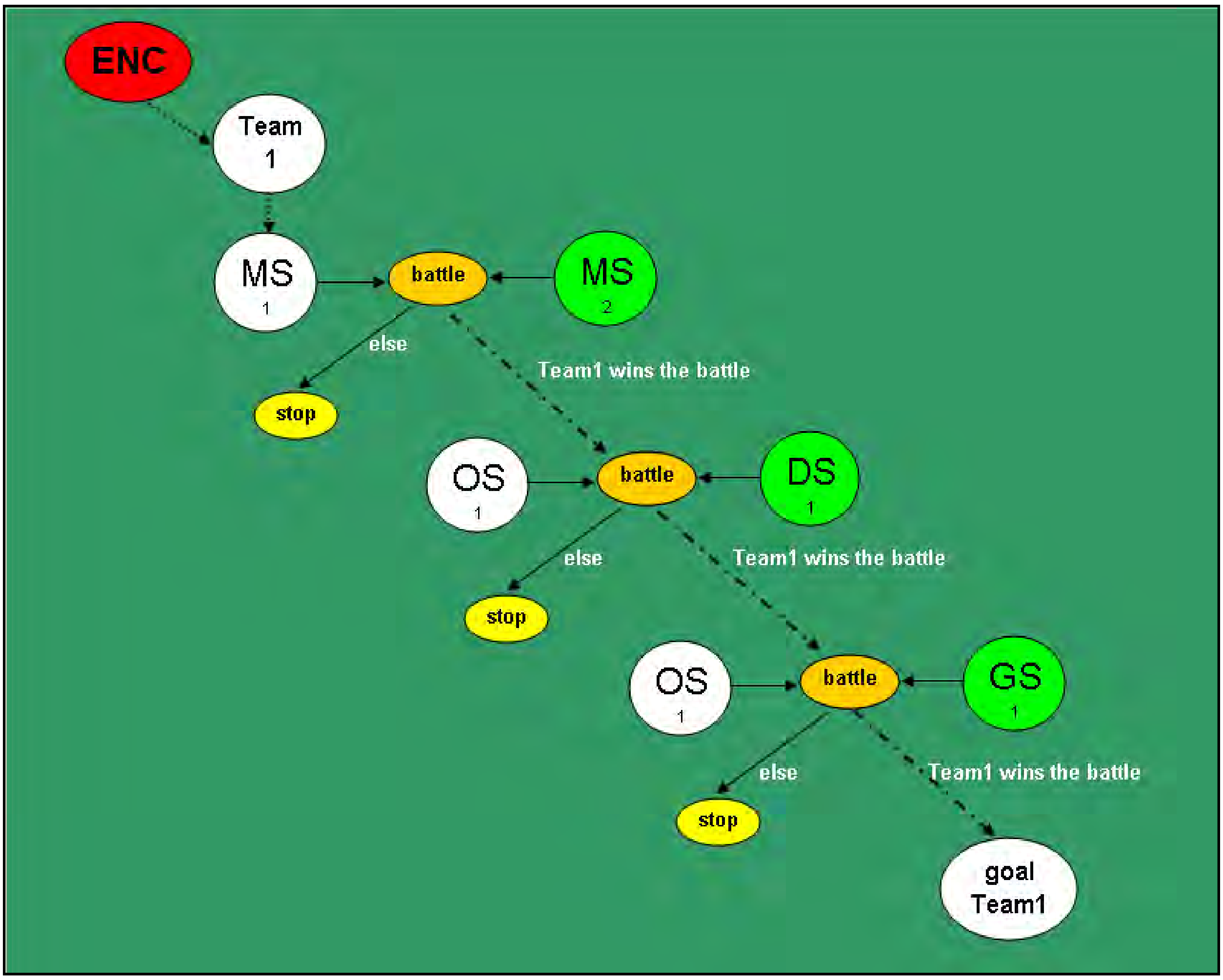

Fig. 1 Exogenous control of a soccer match. Evolutionary Network Control (ENC; top left) acts at the beginning of the match by optimizing the parameters of one team so that successive game theory battles tend to be won by the optimized team.

It can be seen in Fig. 1 that each action is a bunch of three game theory battles. Hence, the a priori control model must be on top of mastering (optimizing) the outcomes of 100 actions, each being a set of several battles. It's clear that this not an easy task, and it requires an advanced type of global optimization.

Instead, the endogenous control allows to change team parameters at each single battle (Fig. 2). For instance, team strategy and game style can be optimized at each single battle.

Fig. 2 shows that the endogenous control is more flexible as it can operate at each level of each single action. Of course, this determines the fact that the endogenous control is much more intensive from a computational viewpoint.

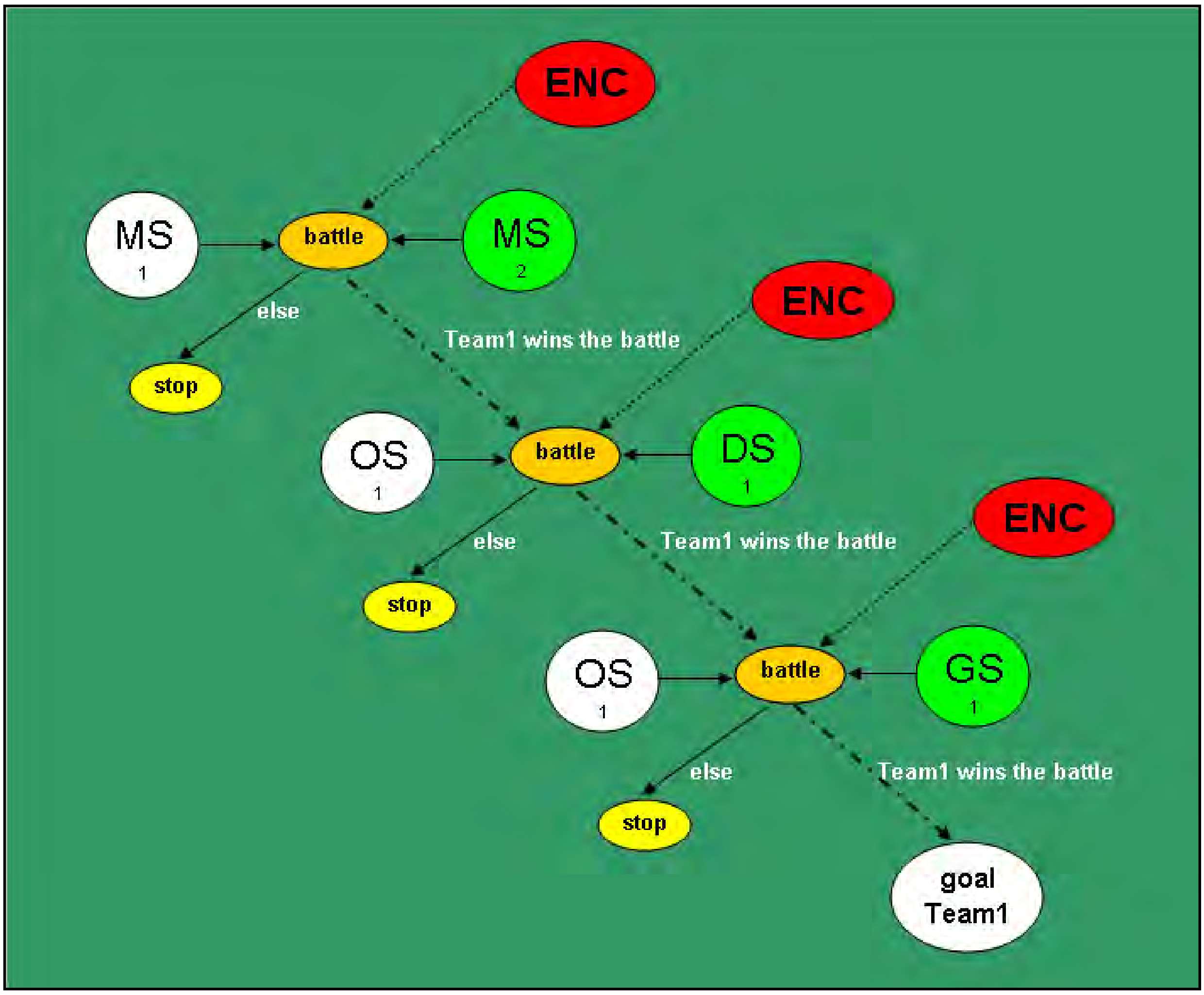

Fig. 2 Endogenous control of a soccer match. Evolutionary Network Control (ENC) acts at each game theory battle so that successive game theory battles tend to be won by the optimized team.

These two approaches (endogenous and exogenous control) reminds of course the two approaches adopted by ENC in the control of quantitative and semi-quantitative networks (Ferrarini 2013a; Ferrarini 2013b).

4 An Illustrative Example

Let's consider the two imaginary soccer teams of Fig. 3 and the game parameters of Table 1. There are two teams with differently skilled players and different playbooks. The White Team plays a 3-4-3 strategy, while the Green Team plays a 5-3-2 scheme. It follows that the White Team mainly bets on the strength of its strikers to overcome the Green Team. Instead, the Green Team adopts a more prudent and defensive game strategy with 5 defenders.

From a strategic viewpoint, it is likely that the White Team adopts a ball possession (*BP*) type of game where actions are mainly driven by its midfielders. As opposite, it is logical that the Green Team opts for a game strategy through which it can jump the White Team's midfield using counter-attacks and long launches from the defensive players toward the strikers. In other words, the most likely game strategy for the Green Team is counter-attack (*CA*).

Team 1	White Team	Team 2	Green Team
Goalkeeper	**Skill**	**Goalkeeper**	**Skill**
G1	8	G1	7.5
Defenders		**Defenders**	
D1	9	D1	8.5
D2	8	D2	8
D3	9	D3	7
		D4	7.5
		D5	9
Midfielders		**Midfielders**	
M1	7.5	M1	9
M2	8	M2	9
M3	9	M3	9.5
M4	7.5		
Strikers		**Strikers**	
S1	8.5	S1	8
S2	7.5	S2	7.5
S3	9		

Fig. 3 Two imaginary soccer teams with differently skilled players and different playbooks.

Table 1 Game parameters.

Game parameters	White Team	Green Team
Field factor (*FF*)	**0**	**0**
Trainer Skill (*TS*)	**1**	**2**
Players experience (*PE*)	**3**	**2**
Athletic decay (*AD*)	**0.50%**	**0.15%**
Game style (*GS*; *1*= ball possession, *2*= counter-attack)	**1**	**2**

The two teams play on a neutral field (*FF*=0 for both teams). The White Team is superior for the experience of its players. The Green Team has better trainer skill and athletic condition, i.e. its players' performances will decrease less as the match proceeds. *Soccer-Decoder* first calculates the overall parameters for each team (Table 2).

Table 2 Overall game parameters.

Game parameters	White Team	Green Team
defensive skill (*DS*)	**46**	**57.75**
midfield skill (*MS*)	**36**	**31.5**
offensive skill (*OS*)	**45**	**33.25**

Now I'll simulate just 1 soccer match (Table 3). The match is predicted to be a draw. Since the White Team plays a *BP* game style, 55 out of 100 of its actions have been stopped by the opponent midfield. Instead the Green Team, which plays a *CA* game style, has been prevalently stopped by opponent defence (66 times out of 100). The White Team has shot 3 times (besides its goal), the Green Team 6 times (besides its goal; Table 3). This suggests that the strategy adopted by the Green Team is effective, but the low value of its *OS* (i.e., 33.25) has precluded its chance to score.

Table 3 Results of the simulation of one soccer match between the White Team and the Green one.

Simulation of 1 inertial match	**White Team**	**Green Team**
goals	**1**	**1**
goals by defenders	**0**	**0**
goals by midfielders	**0**	**1**
goals by strikers	**1**	**0**
actions blocked by opponent midfield	**55**	**27**
actions blocked by opponent defence	**41**	**66**
actions blocked by opponent goalkeeper	**3**	**6**

Now I'll simulate 1000 soccer matches between the two teams. Depending on several parameters, each match is the result of about one thousand game theory battles. This means that the simulation of 1000 matches requires about 1 million battles to be calculated. Results are showed in Table 4.

Table 4 Results of the simulation of 1000 matches between the White Team and the Green one.

Simulation of 1000 inertial matches	**White Team**	**Green Team**
won matches	**590**	**190**
drawn matches	**220**	**220**
lost matches	**190**	**590**
scored goals	**2142**	**1213**
opponent goals	**1213**	**2142**
most likely result	**2**	**1**

After 1000 simulated matches, we can conclude that the White Team has a probability equal to 59.0% to win the match (22.0% of getting a draw, and 19.0% of losing the match).

The most probable outcome is that the White Team wins by 1 goal (232 times out of 1000; Fig. 4). The second one is a draw (220 times; Fig. 4). The most probable positive results for the Green Team is a victory by 1 goal (111 times out of 1000; Fig. 4).

The most likely match result is 2-1 for the White Team (108 times out of 1000; Fig. 5). The second most probable result is 1-1 (94 times out of 1000; Fig. 5).The third one is 2-0 for the White Team (77 times out of 1000; Fig. 5). The most probable positive result for the Green Team is 2-1 (48 times; Fig. 5) followed by 1-0 (39 times; Fig. 5) and 2-0 (20 times; Fig. 5).

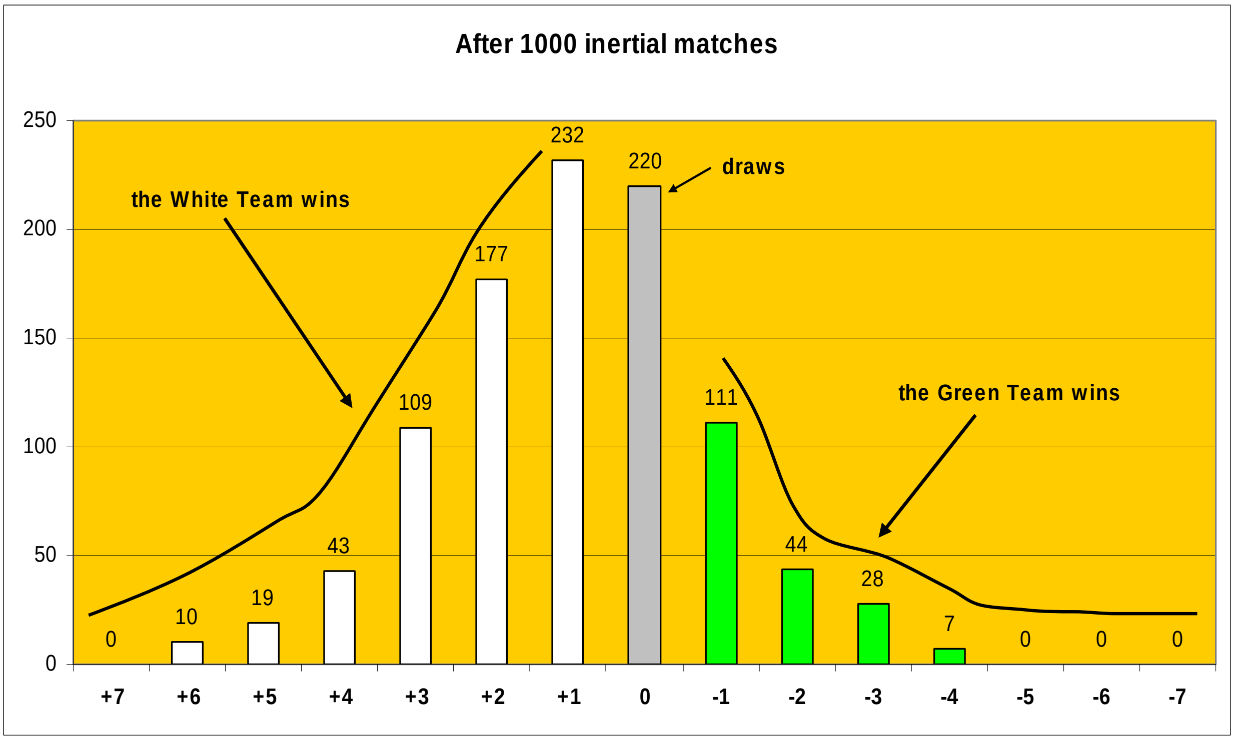

Fig. 4 Difference in the scored goals in the 1000 simulated inertial matches.

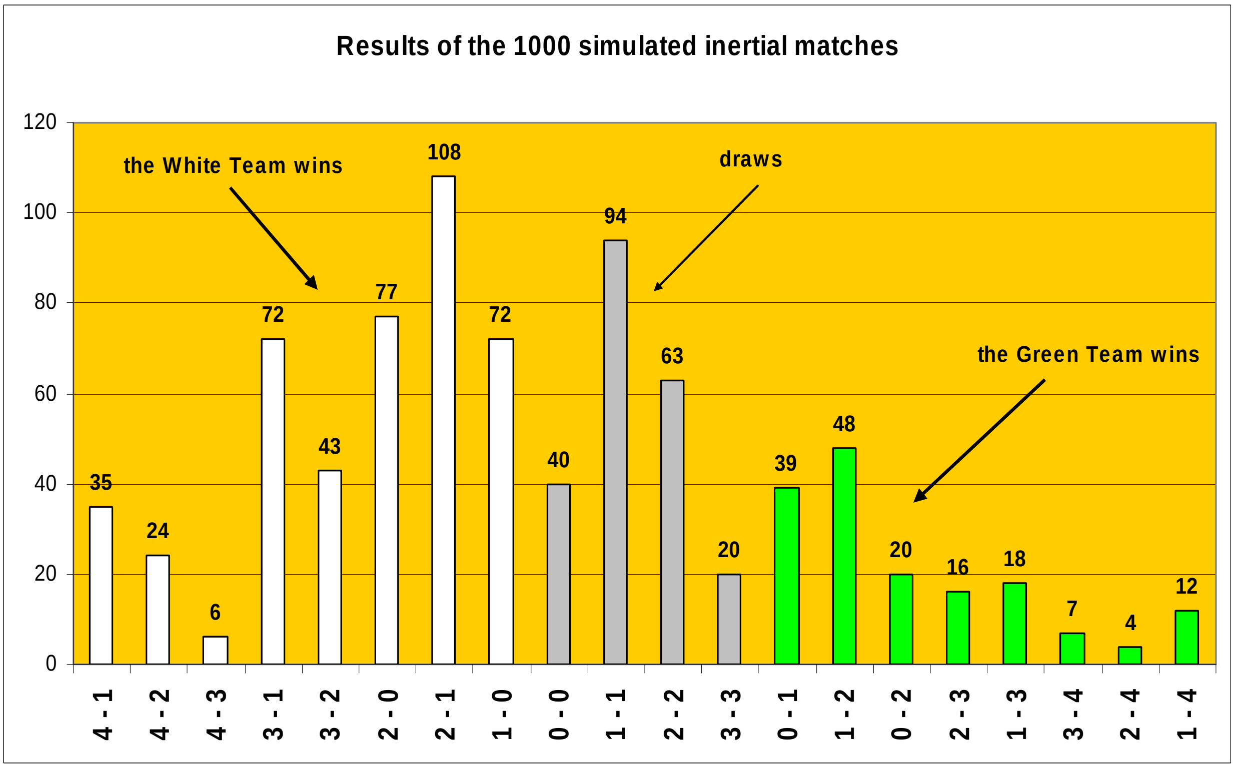

Fig. 5 Results of the simulated inertial matches. The most probable results is 2-1 for the White Team (108 times out of 1000 matches).

Now, I'll join ENC with *Soccer-Decoder* with the purpose of increasing the probability of victory for the Green Team using exogenous control.

Soccer-Lab has found several interesting solutions. By changing game style of the Green Team (from *CA* to *BP*), improving its athletic decay up to 10% and shifting the defender *D5* among the midfielders (4-4-2 tactic), the results of the simulation of 1000 matches are as in Table 5.

Table 5 Results of the 1000 optimized matches between the White Team and the Green one.

Simulation of 1000 inertial matches	White Team	Green Team
won matches	**197**	**661**
drawn matches	**142**	**142**
lost matches	**661**	**197**
scored goals	**1688**	**3062**
opponent goals	**3062**	**1688**
most likely result	**1**	**3**

It results that the inertia of the challenge between the two team is completely passed on the side of the Green Team (661 won matches out of 1000; most probable result: 1-3). This game solution requires 3 little changes (game style, game strategy and athletic improvement) to the Green Team, hence it represents a realistic solution to the search for winning game strategies.

By changing game strategy (from *CA* to *BP*) and shifting the defender *D5* among the midfielders (4-4-2 tactic), the results of the simulation of 1000 matches are as in Tab. 6. This game solution is similar to the first one, but it does not require an athletic improvement of the Green Team. The game inertia is largely on the side of the Green Team, by the way it can be observed that the improvement of the athletic decay from 15% to 10% (not used in this simulation) contributes a lot, in fact the number of won game has decreased to 515 and the most probable result is now 2-2.

Table 6 Results of the 1000 optimized matches between the White Team and the Green one.

Simulation of 1000 inertial matches	White Team	Green Team
won matches	**281**	**515**
drawn matches	**204**	**204**
lost matches	**515**	**281**
scored goals	**1808**	**2367**
opponent goals	**2367**	**1808**
most likely result	**2**	**2**

It is interesting to note that changing only game strategy (from *CA* to *BP*) is not enough to guarantee better chances of victory to the Green Team (Table 7).

A similar inadequate result is achieved by changing game strategy (from *CA* to *BP*) and setting the athletic decay to 5% of the Green Team (Table 8). It's clear that changing game style from *CA* to *BP* also requires the midfield to be strengthened, this is the reason why only the change of tactic from 5-3-2 to 4-4-2 allows to achieve the best results for the Green Team.

Table 7 Simulation of 1000 matches after changing the game strategy (from *CA* to *BP*) of the Green Team.

Simulation of 1000 inertial matches	White Team	Green Team
won matches	**521**	**265**
drawn matches	**214**	**214**
lost matches	**265**	**521**
scored goals	**2045**	**1416**
opponent goals	**1416**	**2045**
most likely result	**2**	**1**

Table 8 Simulation of 1000 matches after changing the game strategy (from *CA* to *BP*) of the Green Team, and setting its athletic decay to 5%.

Simulation of 1000 inertial matches	White Team	Green Team
won matches	**399**	**380**
drawn matches	**221**	**221**
lost matches	**380**	**399**
scored goals	**1798**	**1821**
opponent goals	**1821**	**1798**
most likely result	**1**	**1**

5 Conclusions

Game theory, also known as interactive decision theory, is an umbrella term for the logical side of decision science, including both human and non-human events.

In this paper, a new game theory model given by the combination of *Soccer-Decoder* and Evolutionary Network Control has been introduced in order to tame complex human events like soccer matches. The joining of these two scientific algorithms can answer the following questions:

1) which is the most likely result of the soccer match under study?
2) what happens if a parameter of the game strategy is changed?
3) which game parameters must be optimized, and how, in order to determine the desired game result?

The software *Soccer-Lab* has been realized in order to apply the above-depicted game theory model.

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