Strictness vs. flexibility: Simulation-based recognition of strategies and its success in soccer

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Abstract

Introduction: Recognition and optimization of strategies in sport games is difficult in particular in case of team games, where a number of players are acting "independently" of each other. One way to improve the situation is to cluster the teams into a small number of tactical groups and to analyze the interaction of those groups. The aim of the study is the evaluation of the applicability of SOCCER© simulation in professional soccer by analyzing and simulation of the tactical group interaction.

Methods: The players' positions of tactical groups in soccer can be mapped to formation-patterns and then reflect strategic behaviour and interaction. Based on this information, Monte Carlo-Simulation allows for generating strategies, which – at least from the mathematical point of view – are optimal. In practice, behaviour can be orientated in those optimal strategies but normally is changing depending on the opponent team's activities. Analyzing the game under the aspect of such simulated strategies revealed how strictly resp. flexible a team follows resp. varies strategic patterns.

Approach: A Simulation- and Validation-Study on the basis of 40 position data sets of the 2014/15 German Bundesliga has been conducted to analyze and to optimize such strategic team behaviour in professional soccer.

Results: The Validation-Study demonstrated the applicability of our tactical model. The results of the Simulation-Study revealed that offensive player groups need less tactical strictness in order to gain successful ball possession whereas defensive player groups need tactical strictness to do so.

Conclusion: The strategic behaviour could be recognized and served as basis for optimization analysis: offensive players should play with a more flexible tactical orientation to stay in possession of the ball, whereas defensive players should play with a more planned orientation in order to be successful. The strategic behaviour

of tactical groups can be recognized and optimized using Monte Carlo-based analysis, proposing a new and innovative approach to quantify tactical performance in soccer.

KEYWORDS: STRATEGY, KPI, OFFENCE DYNAMICS, BALL CONTACT, SPACE CONTROL, CORRELATION, EFFICIENCY.

Introduction and theoretical Framework

Currently, different tactical approaches for position data in soccer are discussed (for a recent review see Low et al., 2019). Here, 77 different methods for evaluating collective tactical behaviors are reviewed. Important for this study is the concept of ball possession football, one of the best investigated topics in research, applied science, and club soccer (Memmert & Raabe, 2018), but surprisingly so far with mixed results (for an overview, see Kempe, Vogelbein, Memmert, & Nopp, 2014). While one working group has been submitting data for years showing that ball possession is positively related to the outcome of soccer matches (cf. Casal et al., 2017; Sarmiento et al., 2014b), another working group was unable to confirm these correlations regularly (cf. Stanhope, 2001, Collet et al., 2012). The reasons could be that soccer is a very complex game with many interactions and different environment conditions (e.g., team strength, player performance, game luck, coaching, etc.).

Perl (2018) suggested a simulation approach for soccer, a new method for studying tactical behavior in complex settings. So far, simulation studies are rare in soccer. One example is the probabilistic movement model by Brefeld et al. (2018) which uses the players positions, directions and velocities, to simulate space control. It combines simulation of the players' position for a given time with the resulting zones of control. The aim of the present study is to demonstrate that the simulation based approach by Perl (2018) is a usefull tool to study the complexity of tactical behaviour in soccer.

The players' positions of tactical groups in soccer can be mapped to formation-patterns and then reflect strategic behaviour and interaction (Perl, 2018; Memmert, Lemmink, & Sampaio, 2017). Such tactical formations (or "constellations") are used in order to achieve success in football like scoring goals, ball win, ball possession or space control (Memmert & Raabe, 2018). A strategy of a team can be said to be a guideline for how to choose or change constellations in the interaction with the opponent team (Rein & Memmert, 2016). Those strategies can be simulated using mathematical approaches like Monte Carlo-simulation and game theory to generate optimal strategic patterns (Perl & Memmert, 2018a,b).

However, as is pointed out in Perl (2018), a (mathematically) *optimal* strategy normally consists of a variety of partial strategies, each depending on game situation, involved players, and opposing tactical behaviour. The following example gives an idea of how such a system of main- and sub-strategies could look like.

Consider the situations (points in time) where the attacking group of a team has ball possession. Different types of acting are possible, e.g:

(1) Conserving ball possession; possible reasons:

- improving attacking group constellation
- waiting for better attacking conditions

(2) Build attack; possible reason:

- improved space control

(3) Fast attack; possible reason:

- ball and attacking player close to goal

(4) Playing the ball directed to the goal; possible reason:

- attacking player is reaching a good position close to the goal

(5) Ball back to the goal keeper; possible reason:

- no chance for a successful attack

While the players have to decide in the situation and in a split second how to act, the simulation can use lots of data from different games and situations to find the optimal distribution of chances and therefore – for instance – could calculate the following recommendation:

Use strategy (1) in 50% of those situations / points in time.

Because of its dominant rate, such a strategy can be called *main* strategy, while the remaining strategies with (significant) smaller rates are called *sub*-strategies. In the example from above the distribution of sub-strategies could be as follows

strategy (2) by 20%,

strategy (3) by 20%,

strategy (4) by 5%,

strategy (5).by 5%.

For complex team games like soccer, however, such mediation is much too difficult, since all players involved in a situation must have the same perception and strategic understanding. More practical is the mediation of player group-specific tactical variations, which is meant as follows:

At each point in time a tactical group shows a players' constellation depending on its tactical plan and the opponent team's behaviour. With changing situation normally also that constellation changes, which can be interpreted as a tactical action. Along a playing process those changes build specific patterns, which can be understood as strategies. In turn, such strategies could be used to generate optimal tactical patterns. But also such strategies normally are too complicate to put into practice.

Instead, a main strategy can be generated, which gives room for situation-depending variations. Regarding the main strategy, the number of those variations can be smaller or larger, respectively defining a percentage degree of strictness S or flexibility F : $S + F = 100$. Note that such a main strategy always is specific for just one type of success like e.g. space control. One example of a very strict space control strategy is the well-known "Tiki Taka". An example of a successful flexible counter strategy is "fast counter-attacks".

Using the data of a real game, the optimal main strategy for a given type of success can be calculated using Monte Carlo-simulation. This simulated behaviour normally defers from the observed one. The results presented below show that the simulative changes of the S - resp. F -values can approximate the original success-profile quite precisely, this way producing likely values of strictness and flexibility.

In the Simulation- and Validation-Study, 40 position data sets from professional soccer games have been analyzed in order to find the original main strategies, simulate the optimal main strategies and compare the values of strictness and flexibility.

Given the recorded and the simulated values, soccer experts evaluated those results based on video analyses to show the applicability of SOCCER© simulation to professional football. The study also aims to determine successful tactical behaviors of offensive as well as defensive tactical groups of players.

Method

The position data from the 2014/15 German Bundesliga season were used for verification and evaluation using simulative and network-based process analysis. The selected sample of $N = 10$

matches with 20 teams, each with a offensive and defensive formation was taken by expert football coaches (UEFA A-license) based on the tactical orientation of the participating teams. In accordance with the data pool strategy by Memmert and Raabe (2018) to avoid substitution effects and tactical formation bias, only the first half of the games were used, thus, at the end we have $N = 40$ position data-sets. Each team in the sample played in the selected matches in an offensive formation with a four-man defensive line, two defensive midfielders, a central offensive midfielder, two wingers, and a forward, thus in a 4-2-3-1. The defensive formation of all teams is a 4-4-2.

The intention is to simulate the interplay between the tactical groups of both teams. Therefore, the tactical groups, offensive and defensive, are first determined for both teams. In accordance with Perl and Memmert (2011), for the offensive, the players 6, 7, 8, 9, 10, and 11 are selected. Based on the offensive formation 4-2-3-1, the players 6 to 11 are all players without the four players defensive line. In this study, the defensive is formed with the players 2, 3, 4, 5, 6, 7, and 8 (for a similar procedure, see Memmert & Perl, 2009). The goalkeeper is disregarded here. The positional constellations of these groups are recorded per second and reduced to about 10 - 20 characteristic types with the use of the SOCCER© neural network (see for more details, Perl & Memmert, 2011; Perl, Grunz, & Memmert, 2013). To achieve this, the constellation data (per team and tactical group) are trained on a network, which generates clusters of similar constellations during the training process, thus characterizing the constellation types.

In the simulation, the actual game action is replaced by the interaction between these constellation types. Several performance indicators (see Perl & Memmert, 2017) such as ball contact, space control, or pass-game can be used to evaluate success (Memmert & Raabe, 2019). Because of the high number of occurrences of "ball contact" in a game and because ball contact often plays a central role in strategic plans, this study evaluates success by using ball contact as performance indicator.

The core of the analysis consists of a comparison between the success-oriented recommendation that is derived from strategy optimization on the one hand and a Monte Carlo-simulation of the actual tactical behaviour on the other hand. The "planning rate" or "strictness" then is defined by the percentage of coincidence between actual and recommended behaviour – i.e. the percentage with which the calculated primary strategy ("plan") is implemented in the game. The complement to the planning rate S is the flexibility rate F : $S + F = 100$. The flexibility rate ("creativity") measures the percentage with which the primary strategy is deviated from by tactical variations depending on the situation.

Note, however, that a high planning rate can lead to a stereotypical game that can easily be recognized by the opponent. In the opposite case, a decreasing planning rate can initially increase flexibility (as a criterion for creativity; cf. Memmert, 2015) in tactical behaviour, but if the values are too low, this in turn can lead to an aimless behaviour.

Validation-Study

The selected sample of matches was evaluated by three football experts based on the tactical orientation of the participating teams. Given the strategic plan of each team, the tactical orientation (strategic plan / no strategic plan) of each team was raised by every second for both teams. Through this, a percentage degree of strictness or flexibility was given. The interrater correlation was calculated with Cohens Kappa. A very high interrater correlation was given above the value of 0.95 and a high correlation above the value of 0.90. The average percentage degree of strictness (= planning rate) of all three experts was compared to the SOCCER-data with a correlation analysis.

Moreover, basing on those first results, the analysis software is planned to be completed by tools

for detecting phases of particular high or low strategic strictness and parts of high or low reliability.

Simulation-Study

The simulation by SOCCER© provides a distribution table for each success parameter individually. These distribution tables show the simulated success values of both teams in a 10 x 10 matrix. On the Y-axis the flexibility of team A is shown from 0 to 100 in the form of the planning rate and on the X-axis the flexibility of team B, also from 0 to 100. The simulated numbers of successful events of the given success parameter (ball contact) per halftime are shown as the success values: The higher the value the more successful.

Fig. 1 shows the success values for the selected performance indicator (ball contact) and depending on the planning rates on the left for Team A and the right for Team B. Every success value shows the simulated numbers of successful ball contacts for each team. The tables in the second row show the positive or negative results of both teams as differences of the respective performance values depending on the respective planning rates. In the next step, the threshold values of the flexibilities are determined.

These threshold values are located where the positive performance difference values of a team change into negative values, i.e. the balance points of the optimal 0-sum-distribution, where the performance values of both teams are (approximately) equal, marked here by the red lines for A and B.

Fig. 1: Example screenshot of distribution tables created by SOCCER (©Jürgen Perl). The X-axis shows the strictness of team B from 0 to 100 (planning rate) and the Y-axis the strictness of team A. Tables at the top show the simulated numbers of successful ball contacts of team A (left Table) and team B (right Table). The Tables below show the differences of the respective performance values depending on the respective planning rates (left Table difference A – B & right Table B – A). The threshold is marked by the red line.

Usually, a winning value is defined for a strategy: If, in case of two players, the first player has a winning value greater than the winning value of the second player then the first player will win if following his optimal strategy. The definition of "win" depends on the game: In dicing, "win" normally depends on the thrown numbers.

In soccer, for example, time-specific percentage of success situations like space control or ball contact can define the "win". Such success rates are important under the aspect of reaching strategic aims but do not necessarily mean a probability of winning the game (e.g. if the strategic aims were wrong).

In the mathematical game theory, these winning values are normalized to the median value (in the example of space control: 50%), so that the positive win of one partner is equal to the "negative win" of the other. I.e. the sum of the winnings of both partners is always "0" (therefore 0-sum game). If both partners are "equally strong" and both play their optimal strategy, then for both the winning value is 0, and the result can therefore only be "0" for both (saddle-point strategy). This means: If one of the partners tries to increase its winning value by deviating from its optimal (!) strategy, it will inevitably reduce its winning value if the opponent is optimal. In Fig. 1 the red line marks the saddle point course, i.e. the balance points between win and loss.

In the tables in Fig. 1 and in the following text, absolute numbers but similar results are used without the normalization mentioned above. For a team, these threshold values are therefore - depending on the respective planning rate of the opposing team - the smallest positive result values, i.e. the guaranteed success, at the chosen own planning rate. The threshold values thus characterize the basic tactical approaches of the teams between plan orientation and flexibility and thus provide the basis for the following evaluations. The established threshold values of all 40 position data sets are first averaged as a collective parameter and the corresponding standard deviations are calculated. This is also the procedure for Bundesliga Team A (five games) and Bundesliga Team B (five games) for offensive player groups (players 6 to 11) and defensive player groups (players 2 to 8).

Results

Validation-Study

Eight-point-three percent of the inter-rater reliabilities (Cohens Kappa) were very high and 27.7% were high. In total there is a mean average inter-rater reliability of 0.85 which is above the critical value of 0.80.

The average planning rates of four matches with two teams, respectively (N=8), were all correlated with the pairing Expert planning rates shown as the eight data points in Fig. 2. The minimum averaged planning rates evaluated by the Experts is 45.5, the maximum is 82.0 with a Median value of 57.7. The averaged SOCCER planning rates for offensive and defensive player groups are between 0 and 60 with a Median value of 25. Fig. 2 shows the correlation between the planning rates developed by the Experts and the SOCCER© planning rate.

Fig. 2: Correlation between SOCCER© planning rate and expert planning rate. The X-axis shows the planning rate evaluated by the Experts from 0 to 90. Y-axis shows the planning rates evaluated by SOCCER© from 0 to 90 for each game. Both show mean planning rates of offensive and defensive player groups.

Far more important, results demonstrated that there is a medium to high correlation between the SOCCER© planning rate and expert planning rate ($r = 0.79$).

In Fig. 2 the SOCCER© planning rate shows higher values than planning rates evaluated by experts. On the one hand, the SOCCER© software produces a substantial offset in the planning rate because of the consideration of all available data points of the matches without different kinds of attention foci. It analyses every position of the defined player groups in every moment of the game and processes these through simulation to planning rate values. On the other hand, experts have to evaluate the complex movement of the players and value some characteristic situations higher than other situations because of the individual attention focus and memory ability by the experts. Thus, the offset in Fig. 2 comes from the limited perception of the experts in comparison to the algorithm. The perception of the expert cannot be perfect on all positions in each moment which explains lower planning rate values due to lower information input ability in comparison to SOCCER©.

Simulation-Study

The results of the threshold evaluation of the entire sample show a very high dispersion, as shown in Fig. 3 by the standard deviation. This is equally evident in the analyses of the threshold values for defensive (Fig. 4) and offensive player groups (Fig. 5). As Figures 4 and 5 show, however, the threshold values of offensive and defensive formations follow a similar pattern and increase with a higher own planning rate, i.e. lower flexibility share. In contrast, the successful areas of defensive and offensive player groups behave in opposite ways. With a low own planning rate (0) the successful spectrum of defensive formations is smaller than with a high own planning rate (100). The successful spectrum of defensive player groups can be seen below the threshold graphs in Fig.3,4 and 5. The successful spectrum of offensive player groups is shown above. The graphs in these Figures are equivalent to the red line in Fig.1. Defensive player groups are more successful than the opponent offensive (positive values in Fig.1) below these graphs and offensive player groups above.

Fig. 3 Average thresholds of all games of the sample with the performance indicator ball contact. The X-axis shows the average planning rate value from 0 to 100 for the whole sample. Y-axis shows the threshold value from 0 to 120 (max value 100). The data points describe the average threshold for any given planning rate combination of all games in the sample. The area below the respective threshold value curves describes the planning rate ranges in which the defensive team groupings are more successful

and the area above the respective threshold curves the more successful planning rate combinations of the offensive player groups (success indicator: ball contact).

Fig. 4: Average threshold values of the defensive player groups of both teams. The X-axis shows the average planning rate value from 0 to 100 for the whole sample. The Y-axis shows the threshold value from 0 to 100. The data points describe the average threshold for any given planning rate combinations of all games in the sample. The area below the respective threshold value curves describes the planning rate ranges in which the defensive team groupings are more successful (success indicator: ball contact).

Fig. 5: Average threshold values of the offensive player groups of both teams (A vs. B). The X-axis shows the average planning rate value from 0 to 100 for the whole sample. The Y-axis shows the threshold value from 0 to 100. The data points describe the average threshold for any given planning rate combinations of all games in the sample. The area above the respective threshold values describes the planning rate ranges in which the offensive team groups are more successful (success indicator: ball contact).

Figures 3, 4 and 5 show that offensive player groups with a high own planning rate have on average less successful ball contacts than with a lower planning rate. The graphs in the figures describe the threshold values of successful to less successful playing behavior of offensive and defensive player groups, with the respective flexibility described by the planning rate. The X-

axis shows the planning rates of the considered player groups (offensive/defensive), the Y-axis describes the planning rates of the competing player groups of all examined matches of both teams. The graphs of Figures 4 and 5 all describe a very similar threshold course. Both Teams have a bigger defensive success range the higher the planning rate value (Fig. 4) and higher offensive success range the lower the planning rate values (Fig. 5).

Discussion

Different approaches aimed to determine the successful tactical behaviour of different team members (for a recent meta-analysis, see Low et al., 2019). The main aim of this study was to evaluate the applicability of SOCCER© simulation in professional football by analyzing and simulation of tactical performance in soccer as a function of the strategic planning rate based on performance indicators like ball contact.

Here, we could validate our tactical model according the golden standard of expert rating. More importantly, the results of our simulation model confirmed the assumption that defensive team groups in possession of the ball should play more planned to achieve more successful ball contacts. More effective ball contacts may indicate a better build-up game. The offensive team groups, however, generate more successful ball contacts in contrast to the defensive ones with more flexibility, regardless of the flexibility of the opponent's defense.

For practical implications, the results can be summarized as follows: offensive players should play with a more flexible tactical orientation to stay in possession of the ball, whereas defensive players should play with a more planned orientation in order to be successful.

Many previous studies with low data sets (see for further discussion Memmert et al., 2019) as the present N = 40 Big data study, validated KPIs (Memmert & Rein, 2018; Memmert & Raabe, 2018) as well as a balanced sample regarding overall team performance did not include the aspect of different performance levels and different game strategies. These aspects can be focused on future studies.

The performance indicator ball contact is the less complex indicator that can be evaluated by SOCCER©. All threshold values are based on the simulated positive ball contacts of both player groups. Other indicators like ball control or passes would give more complex results. SOCCER© detects events like contacts, control, and passes through the position data. This means that ball control and passes can only be tracked by the distance from the coordinates of the ball to the coordinates of the player closest to the ball. Future studies can also focus on the indicators ball control and passes which include also other aspects like time of the ball in the close radius to the player or control of the ball after the pass.

On the basis of the reached aims of simulation-based analysis of strategic behavior, future research should elaborate the aims of planning tactical deviations as strategic flexibility and including those flexible tactical deviations into tactical training.

In conclusion, the strategic behaviour of tactical groups can be recognized and optimized using Monte Carlo-based analysis, proposing a new and innovative approach to quantify tactical performance in soccer. The advantage of the presented simulation method consists of small effort, speed, changeable framework conditions, and access to comparisons compared to previous approaches.

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