



# Modeling

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Jürgen Perl was deceased at the time of publication.

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## 8

### Key Messages

The idea of modeling in sport is to map complex dynamic systems to their essential structures, data, and interactions in order to perform descriptive, prognostic, or planning analyses and calculations.

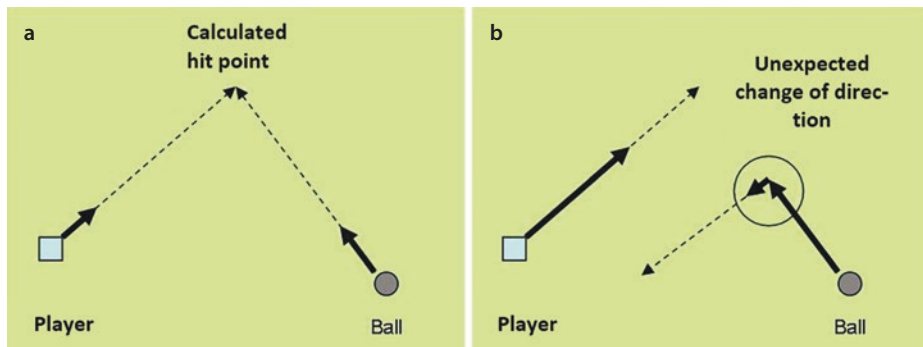
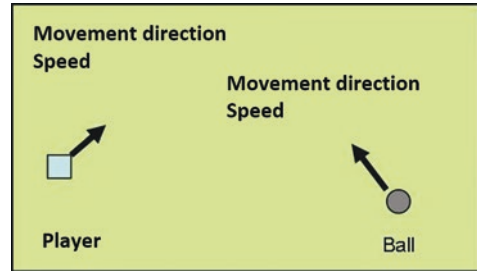
The four essential steps for developing and applying a model are:

- The *reduction* of the real system to its essential components and dynamics.
- The *mapping* of the problem situation to (informatically) manageable objects (numbers, functions, graphs, etc.) taking into account a corresponding back-mapping of the obtained results.
- The *analysis/calculation* is a process of question-oriented information extraction—or in short: the transformation of the problem or input data into result or output data.
- The *visualization* of the results on a system-oriented level (e.g. graphical representation).

## 8.1 Example Sport

Recognition of technical-tactical strengths and weaknesses or the development of strategic concepts based on captured position and action data is essential in soccer (Memmert, 2021). In the following, the case of model-based analysis of player-ball interaction is presented as an introductory example: "Could the player still have reached the ball?" For this purpose, ■ Fig. 8.1 shows a representation or visualization scheme in which the two objects selected in the reduction, player, and ball, are shown with their relevant data for the model (positions of the player and the ball

■ **Fig. 8.1** Visualization of the system reduction



■ **Fig. 8.2** (a) Result of the model calculation. (b) Comparison with reality

with their directions of movement at the beginning of the process as well as velocity values for player and ball from the video data).

The task of the model would now be to answer the input question of reachability from these data by appropriate calculation. The result of this model calculation (or simulation) as an answer to the reachability question would be “yes” or “no” in the simplest case. In both cases, however, the answer remains unsatisfactory because it does not convey where ball reachability occurs or why it does not occur. Thus, as the fourth step of modeling, adequate visualization of the results is necessary.

The calculated path graph shows in ■ Fig. 8.2a that the player theoretically could have reached the ball; but not practically: As the video recordings show, the ball was kicked away by an opponent before the calculated contact time (cf. ■ Fig. 8.2b). But this opponent was not part of the model, i.e. the model had reduced reality too much! And this brings us back to the first and decisive aspect of modeling—the reduction: The “reduction of the real system ...” mentioned above under (1) is necessary to be able to calculate a result at all and with reasonable effort. But it must not be too narrow, in order not to leave out essential objects and dynamics, which influence the result.

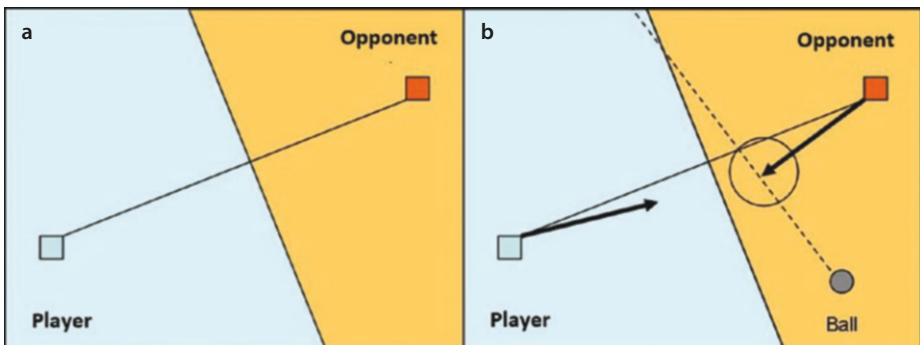
## 8.2 Background

The essential aspect of reduction for the mode of action and usability of a model for the soccer example can be seen in [Fig. 8.2b](#) (Perl & Memmert, 2019): The ball has undergone an abrupt change of motion in its course, which cannot be explained from the model, but is immediately understandable for the observer: the intervention of an opposing player. This opposing player was not part of the model because of too strong reduction, and therefore its possible effect on the motion dynamics to be modelled could not be recognized and calculated.

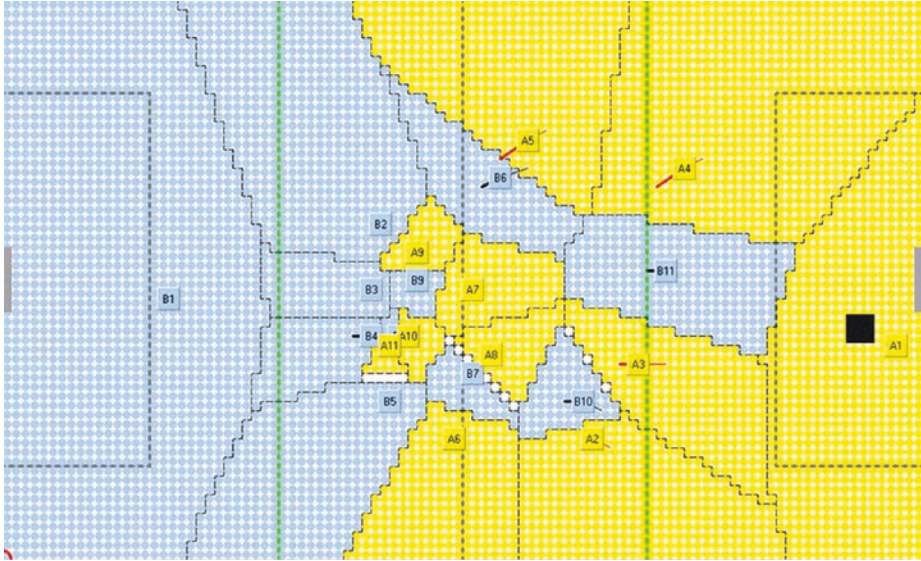
[Figure 8.3a](#) shows the typical modeling of such a player-opponent situation: Assuming that both players move with the same speed, the dividing line between the blue and the yellow area shows all points reached by the blue and the yellow player simultaneously. To all points of the blue area, the blue player reaches faster, to all points of the yellow area his yellow opponent does. These areas of faster reachability are also called the player's Voronoi cell after its "discoverer". The analysis of the reachability of the ball thus becomes more precise to the question (e. g., Rein et al., 2017): "How does the ball pass through the Voronoi cells of the two players?"

[Figure 8.3b](#) shows even if the blue player had moved in the optimal direction, he would not have had a chance to prevent the yellow opponent's action—he could not reach the ball before his opponent. Game analyses based on Voronoi cells are now standard in soccer and are used to analyze the effectiveness of tactical formations in terms of space control (Memmert & Raabe, 2018; Perl & Memmert, 2015) ([Fig. 8.4](#)).

Having thus shown that less reduction can also improve the accuracy of modeling, the question arises: should even more aspects of reality, such as speed differences and changes or changes in movement directions, be incorporated into the model? This question, which is central in modeling, cannot be answered with a



**Fig. 8.3** (a) Players' Voronoi cells. (b) Reachability analysis



**Fig. 8.4** Soccer field with the Voronoi cells of the players of “A-yellow” and “B-blue” (Memmert & Raabe, 2018)

blanket yes or no. The answer depends in each case on the available data, the still justifiable effort, and the expected benefit of modeling and calculation. For example, the aforementioned additions provide the possibility of a technical visualization of the game event parallel to the video presentation—but only if the data are available in sufficient scope and precision. Otherwise, the modeling visualizes the data deficits rather than the gameplay. **Résumé:** The central art of modeling is an adequate reduction that preserves essential dynamics without getting lost in gimmicks (Perl, 2015).

#### Definition

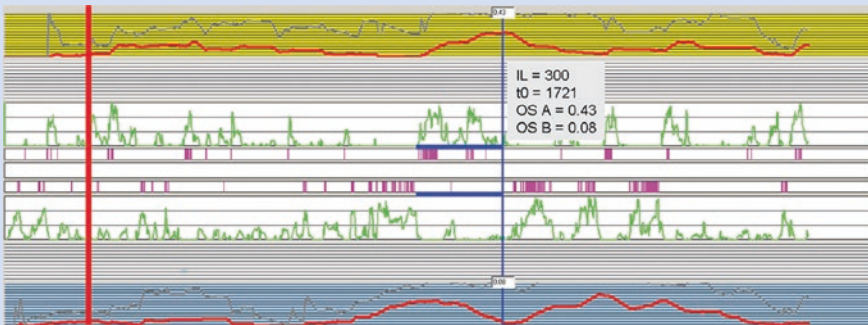
The model is an abstract representation of a system. It is used to diagnose the system state and predict the system behavior (Perl & Uthmann, 1997).

The 4 essential steps of modeling are (soccer example in parentheses):

- System reduction (capturing and representing the player-ball situation)
- Problem mapping (setting of position and velocity data)
- Analysis/calculation (calculation of the running paths and, if necessary, the intersection)
- Result visualization (representation of the player-ball situation as a graph)

### Study Box

The goal of key performance indicators (KPI; Memmert et al., 2017, Low et al., 2019) is to map complex system behavior to single values in order to scale, score, and rank systems or system components. However, very often this mapping only reduces important information about tactical behavior or game dynamics without replacing it with more meaningful information. Perl and Memmert (2017) used a two-step approach to bridge the gap between complex dynamics and numerical metrics in offensive play in soccer. First, they developed a model that visualizes offensive action in a process-oriented manner by using KPIs to represent offensive performance. Second, this model has been organized in terms of time intervals, allowing effectiveness to be measured both for an entire half and for intervals of arbitrary length. In doing so, Perl and Memmert (2017) have shown that the attack efficiency profile is a dynamic indicator of a team's match success. In **Fig. 8.5**, red profiles show how the attack efficiency values of “A-yellow” and “B-blue” for the correlation interval length  $IL = 300$  sec evolve over halftime. The efficiency values (OS A, OS B) for the second  $I0 = 1721$  are plotted in the gray box. In the graph, the green profiles show the respective space control proportions in the opponent's 30-m zone; the purple markers show the ball control time points.



**Fig. 8.5** Progressions of the attack efficiencies for the interval length  $IL = 300$

## 8.3 Application

### ► Example 1

Physiological models for the optimization of stress-performance interactions are used to simulate

- Short-term effects of competition load on performance and fatigue;
- Long-term effects of training load on performance and recovery requirements (Chap. 13).

The central idea of modeling is to reduce the complex physiological interactions to the essential aspects of stress and performance. In this context, the delays with which

load and recovery take effect are the focus of attention: the shorter the recovery delay compared to the load delay, the more developed performance and capability are. Based on these analysis data, training and competition can be improved in their effect (Tampier et al., 2012). If the data expected from the analysis does not match the measured data, this may indicate an irregular training situation such as an unrecognized illness or illicit aids (e.g., doping). ◀

### ▶ Example 2

Tactical-strategic models to represent and analyze player behavior in team games have been used in soccer:

**Formations:** The player distribution of a team or its tactical arrangements can be analyzed by artificial neural networks and thus reduced to a few prototypical formations (Grunz et al., 2012; Perl et al., 2013). With the help of a simulative dynamics analysis of formation changes in specific game situations, tactical behavior patterns can be identified and then, for example, optimized, avoided, or disrupted (the opponent) (Perl & Memmert, 2017). In this context, the modeling of creativity or creative solutions in sports play is also successful (Memmert & Perl, 2009a, 2009b).

**Voronoi cells:** As shown above, Voronoi cells help to analyze the spatial control of players, teams, or tactical groups. Together with ball control, which can be analyzed from the position and movement data of players and ball, one can thus develop models that calculate the efficiency of attacking behavior from the coincidence of space and ball control relative to the players' action effort (Perl & Memmert, 2015). ◀

### ? Questions for the Students

1. How could a physiological stress-performance model be used to identify a doping violation?
2. How accurate must a Voronoi model of a soccer match be?
  - (a) Representation precision in video standard?
  - (b) Approximately, and only for critical phases?
  - (c) In coordination with the analysis requirements?

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