Preparing basketball teams to perform at the highest standard of competition is a complex process dependent upon the interactions of technical, tactical, fitness and anthropometric characteristics of available players. In general, basketball performance depends offensively on shooting field goals and defensively on securing defensive rebounds (Ibáñez et al., 2003; Ittenbach et al., 1992; Karipidis et al., 2001). In closely contested games, fouls and free throws have also been reported to be important (Kozar et al., 1994). Other game-related statistics, such as turnovers, steals, assists and blocked shots, are not reported consistently as discriminators between winning and losing teams. It has also been suggested that the best breakdown of offensive and defensive performances can be obtained by analyzing four factors in the following order of importance: (1) effective field-goal percentage, (2) offensive rebounding percentage, (3) turnovers per ball possession and (4) free-throw rate (Kubatko et al., 2007). This chapter will cover the research on performance indicators addressed in basketball research and how the results of static, dynamic and self-organized complexity studies are contributing to model basketball performance.

Overview of performance indicators in basketball

All persons involved in basketball, at some point, have looked into a boxscore, searching for reasons to help explain the game’s outcome. In general, these boxscores contain information that describes the frequency of actions performed by players of both teams in a game. This description is actually considered a very complete record of the game and provides an idea of how players and teams performed based on the raw data. Therefore, the popularity of basketball statistics with coaches, players, fans and the media should be no surprise.

This massive usage created a need to ensure data reliability – for example, at the time of comparing performances based on data gathered by different operators. In all professional and amateur leagues, the data gathering process is regulated by the operational definitions and criteria published in the Basketball Statisticians Manual (FIBA, 2009). The game actions (variables) presented and defined in this official manual are the following: free throws, field goals, rebounds, assists, steals, turnovers, blocked shots and fouls. This is an excellent contribution to ensure intra- and inter-operator reliability; but by having reliable data, the assump-
tion of validity is not necessarily comprised – that is, although the data may be consistent, it is not obvious that most of these actions are really performance indicators. In addition, there is a major methodological concern related to the contamination of game pace in the frequencies of the gathered variables. For example, the performance of a team A that makes 35 field goals in an 80-possession game must be different to the performance of a team B that makes the same 35 field goals in a 90-possession game. A solution for this problem was found by redefining ball possessions, as described earlier in non-academic websites (i.e. Journal of Basketball Studies) and published later (Kubatko et al., 2007; Oliver, 2004). According to this redefinition, a ball possession starts when one team gains control of the ball and ends when that team gives up control of the ball. The teams can give up possession in several ways, such as making field goals or free throws that lead to the other team taking the ball out of bounds, defensive rebounds and turnovers. Securing an offensive rebound does not start a new possession, although it does start a new play. At the end of the game, ball possessions are guaranteed to be approximately the same for the two teams, providing a normalized basis for evaluating the teams’ efficiency. From this point forward, the points scored per 100 ball possessions were used as a performance indicator, enabling a comparison of performances between games that were played at different paces (Oliver, 2004). In addition, Sampaio and Janeira (2003) normalized all the other variables (rebounds, fouls, assists, etc.) according to the standard measure of 100 ball possessions.

With some of these concerns carefully addressed, the search for valid basketball performance indicators has been a hot topic for several international research teams, either in the academic or in the professional fields. The main aim of most authors was to produce reliable and valid performance indicators and consequently provide their use to coaching staffs for improving player and team performances. The nature of the basketball game is complex, dynamic and non-linear (Davids et al., 2003; Glazier, 2010; Lames and MacGarry, 2007); therefore, the performance indicators used in the modeling process should be able to capture most of these properties. In general, this process can be carried under static, dynamic and self-organized complexity perspectives.

**Static complexity in basketball**

This is the simplest form of complexity, mainly because it assumes that the studied structure does not change with time. The approach analysis of the system is analogous to a photograph (Lucas, 1999). Also, it is a structure-oriented observation model that enables the researcher to register isolated elementary actions of a game, but it does not allow data to be obtained about the process (Pfeiffer and Perl, 2006). Most of the studies carried out in basketball performance analysis have been carried under this approach, with the goal of identifying the variables that most discriminate between winning and losing teams by using the variables’ averages during the 40-minute game (Csataljay et al., 2009; Gomez et al., 2006, 2009; Lorenzo et al., 2010; Ortega et al., 2007; Sampaio and Janeira, 2003; Trninic et al., 2002; Ziv et al., 2010). In very general terms, results show that basketball performance depends offensively on shooting field goals and defensively on securing defensive rebounds (Ibáñez et al., 2003; Karipidis et al., 2001; Sampaio and Janeira, 2003; Trninic et al., 2002). In closely contested games, fouls and free throws have been reported to be important for game outcome (Kozar et al., 1994). Other game-related statistics, such as offensive rebounds, turnovers, steals and assists, are not reported consistently as discriminators between winning and losing teams.

Trninic et al. (2002) studied 36 games from nine final FIBA European Club Championship tournaments. The differences between winning and losing teams were identified in the defensive rebounds, in the field-goal percentages and in free-throw percentages. According
to the authors, the results suggest that winning teams showed better tactical performance in controlling inside positions for defensive rebounds. They were also better at controlling the ball in offense in searching for an optimal chance to shoot, which considerably reduces risks and results in fewer turnovers and higher shooting percentages (Trninic et al., 2002). The same results were found in Junior World Championship games that ended with less than a 12-point margin (Ibáñez et al., 2003). However, these authors obtained different results when analyzing two other groups of games (with differences in scoring between 13 and 24 and above 24 points).

The idea behind this approach of analyzing different groups of games is that analyzing performance according to a static complexity perspective means that several other variables need to be controlled, in order to have not one but several descriptive photographs. For example, a physiological analysis of exercise effects needs an accurate definition of the performed workload (e.g. heart-rate responses to 20 minutes performed in a cycle ergometer at 60 RPM). In basketball, there is a need to describe accurately what kinds of games were analyzed. In the previous physiological example, it makes little sense to analyze a sample mixing workloads performed at 60, 70 and 80 RPM. In fact, this control seems to be one of the most important points of using static complexity models in basketball performance analysis. Thus, the analyzed games should be properly described using several (situational) variables, in order to reduce the variability to comprehensible stages and ensure minimal internal validity.

Subsequent research has attempted to improve the validity of most performance indicators by controlling the effects of several other variables, such as game-score differences (Gomez et al., 2008; Lorenzo et al., 2010; Sampaio and Janeira, 2003), type (Sampaio and Janeira, 2003) and location (Gomez et al., 2008; Sampaio and Janeira, 2003). The game-score difference is an important variable to take into account in the first place. In fact, in static modeling designs, the teams’ performances should be analyzed when the game outcome is still uncertain. For example, a game that ends with a difference of more than 25 points had probably no uncertainty in the outcome (at least in the final minutes) and probably many minutes were assigned to less important players and their actions will be averaged with all the previous ones from the game. Also, when the game is probably lost, the teams trailing in the score take risky decisions, such as systematically forcing three-point field-goal opportunities and ball steals, and they commit a higher number of fouls to stop game time. On the other hand, the teams that lead are now less pressured and just have to control game time. The sum of these decisions favor the leading team, so it seems likely that score differences will probably increase. All these issues are confirmed by substantial differences in all variables between winning and losing teams identified in unbalanced games (Gomez et al., 2006; Sampaio and Janeira, 2003). In fact, in unbalanced games, most of the variables can differentiate between winning and losing teams, but, at the end, they have no practical utility. Therefore, the usage of classification procedures to differentiate between balanced and unbalanced games seems a very adequate procedure.

Game type is an important factor to take into account in basketball teams’ strategic behavior. The regular season is comprised of games played between all teams and it is a contest in accumulating points, enabling teams to reach the playoffs and better classifications (for home-advantage purposes). The playoff games are substantially different. The lowest-level teams are no longer playing and, therefore, each confrontation is always between higher-ranked teams in a series of three, five or seven consecutive games, where the importance of winning is much higher. Therefore, it is no surprise that playoff games may be played slower, with the consequence of having fewer scored points by field goals, due to a less risky strategic behavior. However, committed fouls are higher because it is better to stop the offense immediately through fouling, which leads to more points being scored from free throws and increases the importance of these
statistics. In general, playoff home games are won by teams who exhibit fewer committed fouls and secure fewer offensive rebounds, probably as a consequence of having missed fewer field goals or of a faster defensive repositioning, which prevents players being positioned to secure offensive rebounds. When playing away, winning playoff games seems to be related to missing fewer and making more free throws and securing more offensive rebounds. In these cases, securing offensive rebounds may suggest that away teams succeed in reactivating unsuccessful ball possessions and simultaneously stopping the home team from fast breaking and gaining momentum (Sampaio and Janeira, 2003).

Home advantage in basketball has consistently been between 60 percent to 64 percent (Courneya and Carron, 1992; Pollard and Pollard, 2005). There are several problems with identifying the variables that might be responsible for this effect because it is likely that most causes will be interacting in difficult to ways to isolate and quantify. Although some earlier studies have identified that home teams outperformed away teams in functional aggression variables, such as rebounds, blocks and steals (Varca, 1980), it is not obvious that these behaviors occurred only by the effect of playing at home. Nevertheless, available research relates home teams’ performances to better field-goal percentages, more defensive rebounding and fewer committed fouls (Sampaio and Janeira, 2003). When interacting with game outcome, the home winning teams secured more defensive rebounds and performed fewer assists. Conversely, the away winning teams secured more defensive rebounds, performed more assists and were more successful in two- and three-point field goals (Gomez et al., 2008).

Contrasting winners’ and losers’ performances can only provide a measure of team success at a given instant because successful teams can also lose some games and unsuccessful teams can also win some games (Ibáñez et al., 2008; Madrival and James, 1999). Therefore, other authors have used teams’ classification ranks to measure season-long success (Ibáñez et al., 2008; Ittenbach and Esters, 1995; Ittenbach et al., 1992). The first attempts at relating basketball game statistics to success identified the points per game and the points allowed as the most significant predictor variables (Ittenbach and Esters, 1995; Ittenbach et al., 1992). Although, the results were not surprising, it was interesting to see that the variables used (points per game, points allowed, field-goal percentage, number of free throws, three-point field-goal percentage and number of rebounds) explained less than 50 percent of the variance. In these results, the effect of game pace is clear because a team may score 50 points and be a winner or score 80 points and lose the game. Later on, Ibáñez et al. (2008) aimed to identify the game-related statistics that discriminate between season-long successful and unsuccessful basketball. The obtained results were much different than those obtained when contrasting winners and losers. The most powerful performance indicators were assists, steals, and blocks, highlighting the importance of overall passing skills, as well as outside and inside defensive performance. Curiously, these results are likely to confirm that offensive variables are more related to short-term success (winning games) and defensive variables to mid- and long-term success (winning championships). The probable reason for these results may be the lower variability in defensive performances (Oliver, 2004) because these are less influenced by all environmental factors (such as game location).

More recently, Ziv et al. (2010) analyzed seven consecutive seasons with the aim of examining the relationship between game statistics and team rankings, when controlling for multicollinearity. The results suggested that a number of on-court statistics do not reliably predict team ranking at the end of the season and that condensing the correlated variables can lead to better predictions. The authors used a factor analysis on the 12 on-court variables, which were reduced to three components by a factor analysis. Out of these three components, four new independent variables were created in order to improve the accuracy of teams’ performance analysis: score, condensing assists, field-goal and free-throw percentages; defense, condensing
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defensive rebounding and blocks; gain possession, condensing steals and received fouls; and lose possession, condensing turnovers and committed fouls.

In fact, the search for an accurate group of performance indicators is really a hot topic. It has also been suggested that the best breakdown of offensive and defensive performances can be obtained by analyzing four factors in the following order of importance: (1) effective field-goal percentage, (2) offensive rebounding percentage, (3) turnovers per ball possession, and (4) free-throw rate (Kubatko et al., 2007; Oliver, 2004). Offensively, a team wants to minimize turnovers per possession and maximize all the other factors. These factors are not all equivalent. For example, it was suggested that for NBA games the relative weights of these are approximately 10, 6, 3, and 3, respectively, for each factor (Kubatko et al., 2007).

Sampaio et al. (2010b) analyzed these four factors, attempting to explain the United States of America’s dominance at the Beijing Olympic Games (2008). The authors stated that USA’s fast pace was the main reason for their dominance (81.1 ± 3.0 ball possessions per game versus 70.7 ± 2.1 for the remaining tournament). Therefore, they aimed to identify the game-related statistics that discriminated between fast- and slow-paced games, as well as to identify key performance factors relating to point differentials. The findings indicated that an increase in game pace for the USA team resulted in more recovered balls and a higher number of successful two-point field goals, while not hindering performance substantially in any of the other game-related statistics. In contrast, when the opponent teams increased the pace of the game, only the number of fouls they committed increased. The effects of the four independent variables were inspected for the whole game and for the first- and second-half quarters. For the whole-game model, the outcome was explained by the four factors, but the recovered balls appeared as the second most important factor in explaining the differences in game-quarter scores. For each recovered-ball-per-posses-sion more than the opponent, the USA team increased game quarter outcome by 16.9 ± 5.1 points. These measures of assertive play on both offensive (offensive rebounding) and defensive (recovered balls) play were important factors in the first half but not in the second, indicating that USA’s assertive play diminished in the second half. These results may represent a strategic decision to play more conservatively at the end of the game in order to promote the adequate and needed recovery when facing a concentrated schedule such as the Olympics. Nevertheless, the differences obtained between the first- and second-half quarters help to emphasize that performance do changes with time and, therefore, approaching performance analysis by using dynamic complexity may be an interesting complement to understand the game determinants.

Dynamic and self-organized complexity in basketball

Dynamic complexity allows the dimension of time to be addressed in our understanding of the phenomenon. Often, time is modeled as a continuous variable; however, for this particular situation, the attempts to model the basketball game by using time as a discrete variable will also be considered (although they are not dynamic in a straight sense).

It is a fact that time is a fundamental dimension for understanding basketball performance. Nevertheless, the game is better described by the performance indicators that do not change with time (or do so more predictably). From a dynamic perspective, it is possible to find literature describing the importance of initial strong performances by the early success models (Isoahola and Blanchard, 1986). Other perspectives are that starting to lead the game may be understood as a measure of performance accomplishment and hence might have an effect on players’ subsequent efforts (Bandura, 1997).

Basketball research on this topic is very scarce. Cooper et al. (1992) investigated whether initial and late-game scores are good predictors for the final outcome. It was found that teams who were
winning in the first quarter of the game ended up winning 70 percent of the time, whereas the teams who were winning at the end of the third quarter ended up winning 80 percent of the time. More recently, Sampaio et al. (2010c) found that the greater the difference in accumulated score at the beginning of each quarter, the more points were recovered by the teams who were losing. In these cases, only when differences in score were above eight points did the lead in the game quarter either have a detrimental effect on the winning team or a motivational effect on the losing team, or both. In fact, the results showed that game quarter outcomes in the whole game, in the second, third and fourth game quarters, were explained by the difference in the accumulated score at the beginning of the quarter. For each point of difference in the accumulated score at the beginning of each quarter, the teams decreased game quarter outcome by 0.27, 0.30, 0.21 and 0.29 points, respectively (Sampaio et al., 2010c). That is, if a team was leading by ten points at half-time, the most likely result at the end of the third quarter was for them to maintain only a seven-point lead.

Other perspectives suggest that the last moments of the games are the most determinant (Bar-Eli and Tenenbaum, 1988a, 1988b; Bar-Eli and Tractinsky, 2000). Obviously, in these last moments of the game, all positive actions, like steals or blocks, and negative actions, like fouls or turnovers, acquire an increased importance. In fact, if a team is winning by one point in the final ball possession and manages to block the opponents’ shot, this block may be considered a decisive action. However, it would have much less importance anywhere else in the game. For example, basketball free-throw performance indicators acquire much higher importance in the final moments of these balanced games, where the game is to be decided and the frequency of fouling increases (Kozar et al., 1994). In this study, the authors identified that about 20 percent of all points were scored from free throws. Also, the free throws comprised a significantly higher percentage of total points scored during the last five minutes than during the first 35 minutes of the game, both for winning and for losing teams. The results of Bar-Eli and Tractinsky (2000) were obtained from a sample of 57 ball possessions in the last five minutes of the game indicated that final moments are characterized as comprising twice as many highly critical possessions than low-criticality possessions. Also, the number of highly critical possessions increased strongly toward the end of the game. As should be expected, the results also indicated that highly critical possessions were characterized by a lower quality of decision making compared to low-criticality possessions.

In this topic of criticality, research has also investigated the origin and the validity of common beliefs regarding the ‘hot hand’ phenomenon. Probably the majority of basketball players and fans tend to believe that a player’s probability of hitting a field goal is higher following a hit than following a miss on the previous shot. However, research has systematically failed to provide such evidence (Gilovich et al., 1985). According to Gilovich et al. (1985), the belief in the ‘hot hand’ may be attributed to a general misconception of chance, according to which even short random sequences are thought to be highly representative of their generating process. After several years of research on this topic, a review has been made and, still, the question of whether success breeds success and failure breeds failure remains unsolved (Bar-Eli et al., 2006). In essence, the empirical research supports the non-existence of a relationship between future success and past performance. The authors also point to the need for further developments around the structure of the environment in which a hot hand belief is likely to emerge. As proposed earlier by Burns (2004), an important step forward would be detecting situational factors that enable us to judge the value of the belief either as a fallacy or an adaptive strategy for decision making. In fact, it seems possible that the ‘hot hand’ may be an adaptive behavior flowing from a fallacious belief, suggesting that there should be a connection in the mind of players between the belief and the behavior, and that this connection should be stronger in expert players. Nevertheless, the structure of the environment needs to be considered in order to improve understanding of this topic – for example, by using self-organizing complexity procedures.
Self-organizing complexity aims to combine the internal constraints of closed systems with the creative evolution of open systems (Lucas, 1999). Therefore, the performance in a basketball game is analyzed as a result of co-evolving interactions between the player, the task and the environment (Newell, 1986). The main idea here is the possibility of designing the environment rather than the system itself and letting the system evolve toward a solution, without trying to impose one. At the end, the aim is to predict the emergent solutions that may occur from different configurations and constraints of the environment. Available literature using the game of basketball is very limited. Although speculating without using game data, Schmidt et al. (1999) have described dynamic self-organization and dyadic intra- and interactions, providing several examples from basketball. The authors demonstrated how spontaneous strategic changes could occur – for example, in a backdoor play – and how these could be measured by using variables like the distance of the attacker or ball from the attacking basket and the distance between the defender and the attacker.

Only a couple more studies are available, by Bourbousson et al. (2010a) and Bourbousson et al. (2010b). In the first study, the authors examined space–time patterns of basketball players during competition by analyzing positional data. Strong, coordinated in-phase relations were identified in the longitudinal (basket-to-basket) direction for all playing dyads, suggesting that these movements were very constrained by the game demands. In the second study, the authors examined space–time coordination dynamics of two basketball teams during competition. They used as variables the geometric team center and a stretch index, obtained from the mean distance of team members from the center. Non-linear relative-phase analysis of the centers demonstrated in-phase stabilities in both the longitudinal and the lateral directions, with more stability in the longitudinal direction. Stretch index results demonstrated in-phase attraction in the longitudinal direction and no attraction in the lateral direction. Overall, the findings demonstrated that space–time movement patterns in basketball seem to present a uniform description, in keeping with universal principles of dynamical self-organizing systems. Also, these results may open up interesting perspectives in providing explanations for several results obtained by performance analysis under-grounded in static complexity models.

Concluding remarks

The framework presented in Figure 28.1 resumes this chapter. Basketball performance indicators should be able to capture global or partial aspects of complex, dynamic and non-linear

![Figure 28.1 Complexity and research in the basketball game](image-url)
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<tr>
<td>Bourbousson et al. (2010b)</td>
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properties of performance. Static complexity and structure-oriented observation models enable a higher quantity of isolated elementary actions of a game to be registered. These are suitable for result-description purposes, but limited when there is a need to obtain data about the process. Dynamic complexity modeling has been used to address the time dimension to understand performance either by early success models of criticality or by the final moments of the game (criticality). Finally, self-organizing complexity seems to be emerging, with the need to combine the co-evolving interactions between the player, the task and the environment.

Table 28.1 presents a very brief description of how recent studies are addressing these previously presented issues. In particular, attention should be paid to the criteria used in assessing the performance indicators’ validity and also to the control made by addressing normalization and/or variability.

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