Summary

The term profile has been used in performance analysis of sport to date and this chapter will serve to ensure the word ‘profiling’ is used correctly, as it is in other disciplines such as management and psychology. This chapter explains what a profile is and what a profile is not. It is a collection of related variables brought together to represent an athlete; for example, a fitness profile or a psychological profile. In sports performance, a profile can be used to represent typical performance based on multiple match data. However, a profile can also be used to represent an individual performance. The variables included within sports performance profiles are typically performance indicators. When a profile is produced for a team or athlete, it is necessary to represent the variability in performance indicator values showing where the team or athlete is consistent or inconsistent. This chapter reports on the techniques of James et al. (2005) and O’Donoghue (2005) and the different ways they represent average performance and spread of performances. However, these techniques average different types of performance in a way that conceals important information. For example, one may wish to know how a team or individual performs against different classes of opponent. This issue is addressed in the method of Cullinane and O’Donoghue (2011), which accounts for opposition effect when interpreting performances, leading to the generation of profiles that include sections for different types of matches. The three techniques outlined in this chapter use the same example for purposes of illustration and comparison.

Introduction

The word ‘profile’ has different meanings in different contexts. For example, a profile of a human head, a building or a mountain is a side view of the outline of the head, building or mountain, illustrating distinctive features. Other geographical uses of the word ‘profile’ include vertical cross-sections of soil or rock. A profile of a famous person is a short biographical article or documentary about the person. In computer systems, a profile is computer-readable text allowing a user’s operating environment to be set up when they log on to the computer system. In many areas of scientific research and professional practice, the word ‘profile’ is used to represent a set of data that exhibit significant properties. For example, the profile of a manager can be
characterised by a set of characteristics which should have optimal values (Quinn et al., 1996). These characteristics are displayed on a radar chart (similar to Figure 11.1 in this chapter), allowing the manager to be portrayed in terms of relevant roles. This is the way in which the word is used in sports science. A profile is a collection of variables that characterise a person, organisation or some other entity. For example, a fitness profile for an athlete might contain a collection of anthropometric measurements and fitness test scores (McIntyre and Hall, 2005; Sedano et al., 2009). The purpose of the fitness profile is to represent all of the different components of fitness that are relevant to the particular sport. Similarly, in sport psychology, profiles are used to represent a collection of variables that make up some overall construct or psychological profile (Butler, 1992; Dale and Wrisberg, 1996; Martens et al., 1990; Gucciardi and Gordon, 2009). For example, the profile of mood states is comprised of self-report measures for anger, confusion, depression, fatigue, tension and vigour (McNair et al., 1971). Sports performance profiling methods have included psychological, physical and technical variables. One such method uses radar charts to allow direct comparison of an athlete’s profile with an ideal profile for the athlete’s role (Doyle and Parfitt, 1996). The variables used in such profiles should be valid and reliable, though the reliability of a profile as a whole should also be investigated (Gleeson et al., 2005). Performance profiles have helped athlete awareness of areas they need to improve and general monitoring of performance (Weston et al., 2011). This in turn has helped goal setting and increased the athlete’s motivation to improve.

There are other terms that are used in the current chapter, such as performance, performer and performance indicator. Profiles of sports performance can represent different types of performance. For example, we may wish to analyse an individual match to identify areas requiring attention. Alternatively, we may be characterising the typical performance of a team or individual using data from multiple performances against a range of opponents. Therefore, the word ‘performance’ can be used to refer to an abstract typical performance as well as an observed particular performance. The word ‘performer’ is used to represent a team or individual whose performance in sport is being profiled. The profile comprises a set of variables that together characterise the overall performance. These variables are typically performance indicators that are valid and reliable variables for different aspects of the performance. (For a review on performance indicators and their qualities, see Chapter 10.) Performance indicators in sports performance have similar characteristics to performance indicators in engineering disciplines (Bevan, 1995). The term ‘performance indicator’ is not another name for ‘variable’ but is a term for a variable or variables that are demonstrated to be valid measures of important aspects of performance, and which possess the metric properties of having an objective measurement procedure, a known scale of measurement and a valid means of interpretation (O’Donoghue, 2010: 21).

Sports performance variables are not stable characteristics of performers in the way anthropometric variables are (O’Donoghue, 2004; Gregson et al., 2010). For example, various factors such as venue (Brown et al., 2002; Carron et al., 2005), importance of the match (Hale, 2004) and score-line within the match (O’Donoghue and Tenga, 2001; Bloomfield et al., 2004a, 2004b; Shaw and O’Donoghue, 2004; Redwood-Brown, 2008) influence performance, with the largest source of variability in sports performance resulting from quality of opposition (McGarry and Franks, 1994). Therefore, Hughes et al. (2001) developed a technique to determine a typical value for a performance variable using multiple match data. Essentially, the technique determined how many matches were required for the mean value of the performance indicator to stabilise within a given percentage (e.g. 10 per cent) of the mean for the number of matches from which data were available. Hughes et al. (2001) referred to this as a ‘profiling’ technique, using the word ‘profiling’ in a manner inconsistent with the common description provided above. There are five specific objections to using the word ‘profiling’ to describe the technique developed by Hughes.
et al. (2001). These objections are: (1) The technique is applied to a single performance variable without the possibility of bringing a collection of performance variables together into a performance profile; (2) The technique forces stabilisation of variables in situations where unstable and inconsistent performance exists and needs to be recognised; (3) Stabilisation is based on percentage error, which expresses differences in values as a percentage of the mean of available values. This approach risks division by zero and the possibility of negative percentage errors being calculated with interval scale variables; (4) As matches are added, the percentage error of the evolving mean is calculated using the mean of the data available. This is a sample mean and is subject to sampling error, which has not been addressed (see O'Donoghue and Ponting, 2005); and (5) It is not necessary for multiple match data to be used to produce a profile of a performance. Profiles can be produced for performers where typical performance data from multiple matches is necessary; however, individual match analysis is also important in its own right.

It is the first criticism that is of primary concern, hence the technique of Hughes et al. (2001) will not be considered further in this review on profiling technique. Instead only those profiling techniques that characterise performance using a set of relevant performance indicators will hereafter be addressed.

Four main profiling techniques used in performance analysis of sport are those of James et al. (2005), O'Donoghue (2005), O'Donoghue et al. (2008) and O'Donoghue and Cullinane (2011). These techniques can be used to produce a profile of an individual performance, as well as the typical performance of a performer, and data from the 2010 and 2011 Australian and US Open tennis tournaments are used to compare them. These tournaments were chosen because they used the same Rebound Ace surface since 2010. The 23 matches completed by Novak Djokovic and the 25 matches completed by Roger Federer during these tournaments are used to illustrate different uses of these profiling techniques.

Performance profiles using confidence intervals of medians

The technique

The technique of James et al. (2005) represents a performance as a collection of all relevant performance indicators. The technique determines the median and 95 per cent confidence interval for the median for each performance indicator based on a set of performances. The locations of the lower and upper limits of a 95 per cent confidence interval for the median are

\[ np \pm z_{\alpha/2} \sqrt{np(1-p)} \]

where \( n \) is the number of performances, \( p \) is 0.5 because the quantile of interest is the median and \( z_{\alpha/2} \) is 1.96. James et al. (2005) illustrated the technique using performances of rugby union players from a season of 22 matches. The use of 95 per cent confidence intervals gives the technique two advantages over previous methods. First, the technique recognises that typical performance is produced from a sample of performances and subject to sampling error. Second, the 95 per cent confidence intervals allow performers to be compared to identify those performance indicators where they significantly differ and those performance indicators where any differences could be due to sampling error.

A performer profile

The technique can be used to display a typical profile of a performer, compare the typical profiles of different performers and compare the typical profiles of the same performer under different match conditions, such as home games and away games. The medians and 95 per cent confidence intervals of the medians can be presented in tabular or graphical form. Table 11.1
P. O’Donoghue

compares typical profiles of Novak Djokovic and Roger Federer. The 95 per cent confidence intervals for the players overlap for each performance indicator. The reason for using a table to present these profiles is because the 13 performance indicators use different units (some percentages and some speeds in km.hour\(^{-1}\)) and different ranges of numerical values. The line graph representation used by James et al. (2005) to illustrate the medians of event frequencies was effective. However, for the performance indicators in the tennis example used here, graphical presentation would make it difficult to compare the percentage of service points that are aces or that are double faults between the two players. This is because the medians of these variables are less than 10 per cent, while median values of mean first service speed exceed 180 km.hour\(^{-1}\).

Table 11.1 Performance profiles for Novak Djokovic and Roger Federer for their matches in the 2010 and 2011 Australian and US Opens

<table>
<thead>
<tr>
<th>Performance indicator</th>
<th>Novak Djokovic (n = 23)</th>
<th>Roger Federer (n = 25)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Median</td>
<td>95% Confidence interval</td>
</tr>
<tr>
<td>%First serves in</td>
<td>66.7</td>
<td>65.5–68.6</td>
</tr>
<tr>
<td>%Won when first serve in</td>
<td>74.7</td>
<td>68.9–75.6</td>
</tr>
<tr>
<td>%Won when second serve required</td>
<td>52.8</td>
<td>46.6–61.6</td>
</tr>
<tr>
<td>%Aces</td>
<td>5.0</td>
<td>4.0–7.7</td>
</tr>
<tr>
<td>%Double faults</td>
<td>2.8</td>
<td>1.4–4.8</td>
</tr>
<tr>
<td>%Unforced errors</td>
<td>13.6</td>
<td>12.2–18.2</td>
</tr>
<tr>
<td>%Winners</td>
<td>17.6</td>
<td>13.0–20.3</td>
</tr>
<tr>
<td>%Net points</td>
<td>13.2</td>
<td>8.8–15.5</td>
</tr>
<tr>
<td>%Net points won</td>
<td>66.0</td>
<td>61.9–71.1</td>
</tr>
<tr>
<td>%Break points won</td>
<td>44.4</td>
<td>38.7–54.1</td>
</tr>
<tr>
<td>%Points won when receiving</td>
<td>45.8</td>
<td>39.3–48.0</td>
</tr>
<tr>
<td>Mean first serve speed (km.h(^{-1}))</td>
<td>184.0</td>
<td>180.8–187.2</td>
</tr>
<tr>
<td>Mean second serve speed (km.h(^{-1}))</td>
<td>152.0</td>
<td>148.9–155.1</td>
</tr>
</tbody>
</table>

There are a number of issues that can be discussed in relation to this profiling technique. First, the technique represents typical performance without representing the spread of values about that typical performance. The 95 per cent confidence interval is a confidence interval for the median such that the probability of the true median value being within that confidence interval is 95 per cent. The spread of values for the performer is not represented by this. A second issue is that the 95 per cent confidence interval for the median might be viewed as too stringent to detect differences in technical effectiveness indicators between players of similar world rankings. The matches are played against a range of opponents of differing tactical styles and different technical abilities. For example, Roger Federer played against opponents ranked between 3 and 109 in the 2010 US Open. Even when 20 performances were used to produce a profile, the percentiles used to calculate the lower and upper limits of the 95 per cent confidence interval are 45.6 per cent and 54.4 per cent. Inherently unstable data, such as those in sports performance, can render differences between performers to be non-significant. Consider the percentage of points won when a second serve is required; 52.8 per cent for Djokovic and 60.5 per cent for Federer. A set of 310 player performances from these tournaments can be used to create norms, revealing that Federer’s performance when a second serve was required exceeded that of over 85 per cent of players, while Djokovic’s performance in this situation was in the 5 per cent banding from 55 to 60 per cent. These norms can be used to show a meaningful difference between the two players when assessed against a large set of men’s singles performances from relevant tournaments.
Interpreting performance indicators using quantiles

The technique

At the same time that James et al. (2005) produced a profiling technique based on confidence intervals, O’Donoghue (2005) produced a profiling technique that used quantiles. Quantiles include percentiles and are often used to interpret variables in sports psychology (Martens et al., 1990), fitness (Hoffman, 2006; ACSM, 2010), health (Hulens et al., 2001) and educational performance. For example, the percentiles for body mass index (BMI) of 20-year-old males are 99 values for BMI that partition the population of 20-year-old males into 100 groups containing 1 per cent of that population. The thirtieth percentile for BMI is that value at which 30 per cent of the 20-year-old male population have BMIs lower than that value. Other types of quantiles include quartiles, deciles and vigintiles (O’Donoghue, 2012: 59). O’Donoghue’s (2005) technique used quantiles to evaluate performance indicators in sports performance. This is done by determining the quantile for each performance indicator and plotting it on a radar chart that is a performance profile comprising all relevant performance indicators, as shown in Figure 11.1.

Individual performances

The technique is not suitable for interpreting an individual performance because opposition effect is not addressed. For example, if a tennis player plays a match against the world number 1, the player’s performance indicator values may be low and will map onto low percentiles. Similarly, if the player plays against an opponent ranked outside the world’s top 1,000, performance indicators will be higher and will map onto higher percentiles.
A performer profile

The technique is used to produce a profile of a performer that represents the performer’s typical performance as well as the spread of performances about that typical performance. This is done by using a representative set of performances by the performer against a full range of opponents and determining measures of location and dispersion for each performance indicator. The technique can be used with medians and lower and upper quartiles where the player’s performances show a skewed distribution or with the mean+0.67 standard deviation for each performance indicator. The reason for using mean+0.67 standard deviations is that this range of values covers 50 per cent of values in normally distributed data, which is the same as the inter-quartile range. A range of values from one standard deviation below the mean to one standard deviation above the mean would cover 68.3 per cent of values in normally distributed performances.

The technique demonstrates where some performance indicators have high values while others are low or average. A key property of the technique is that it recognises that a performer may have consistent values for some performance indicators and inconsistent values for other performance indicators. The degree of consistency of a performance indicator for a given performer is something that coaches and opponents need to be aware of, and so this profiling technique, by design, does not force performance indicator values to stabilise. Figure 11.1 is a profile of Novak Djokovic’s 23 performances at the Australian and US Opens in 2010 and 2011. Vigintile norms were determined from 310 performances within the two tournaments, thereby allowing the median, lower and upper quartiles of each performance indicator to be associated within a 5 per cent band. The midpoint of the band (2.5 per cent, 7.5 per cent, 12.5 per cent . . . 97.5 per cent) is plotted on the radar chart in Figure 11.1. The performance profile shows Djokovic’s typical performance within the relevant population of tennis performance, using medians. The player has relatively high values (greater than the values observed in 80 per cent of the performances at the Australian and US Opens) for the percentage of points won when receiving serve, mean first serve speed, mean second serve speed and the percentage of service points where the first serve is in. Furthermore, he makes a relatively low percentage of unforced errors. The inter-quartile range represents the spread of performances about the median. This is interpreted by relating the variability within Djokovic’s performances to the variability that exists in men’s singles tennis in general. In other words, if Djokovic’s inter-quartile range for a variable is similar to the inter-quartile range for men’s singles tennis in general, then there is a similar variability within his performances and the performances between different male players. His most consistent areas were the percentage of service points where the first serve was in and the mean speed of his second serve. The inter-quartile range for each of these performance indicators was equivalent to 10 per cent or less of the spread of performances observed at the tournaments. The most inconsistent areas were the percentage of points won when he required a second serve and the percentage of points won when he went to the net. He had an inter-quartile range of 50 per cent or higher for each of these performance indicators. Therefore, the spread of values for these two performance indicators was greater than or equal to that of the wider population of different players.

A criticism of Figure 11.1 is that performance indicator values are replaced by quantiles. There are performance indicators in many sports that are sufficiently well established that coaches and scientists have a good knowledge of what are high, average and low values. Therefore, an alternative representation to the radar chart is a table that shows actual values for the median, lower and upper quartiles (or mean+0.67 standard deviation) for each performance indicator, as well as the quantiles that these map onto.
Interpreting performance indicators using norms for different types of matches

The use of quantiles to interpret performances is suitable for producing a profile of a performer based on a representative set of matches against a full range of opponents (O’Donoghue, 2005). However, the technique is not recommended for the interpretation of individual performances because performance indicator values and their corresponding quantiles will often be influenced by the quality of opposition. This risks misinterpreting a performance against a higher-ranked opponent as below standard simply because low performance indicator values map onto corresponding low quantiles. Therefore, a further profiling technique was proposed to use separate norms for different types of matches (O’Donoghue, 2006). The different types of matches could include matches against opponents of similar strength, matches against opponents of lower strength and matches against opponents of higher strength. The technique is essentially the same as that of O’Donoghue (2005), except the population of performances used to produce the quantiles is divided into different types of matches. Therefore, a performance against a higher-ranked opponent will be evaluated using quantile norms for this type of match. The technique has been applied using quartiles (O’Donoghue, 2008) and deciles (O’Donoghue et al., 2008). In British National Superleague netball, teams were classified as being in the top half of the league or in the bottom half of the league (O’Donoghue et al., 2008). This meant that there were four different types of performance (Top v Top, Top v Bottom, Bottom v Top and Bottom v Bottom). Therefore, separate norms were produced for these four different types of matches. The approach was also illustrated in women’s singles tennis at Grand Slam tournaments using three groups of players (O’Donoghue, 2008). Group A contained players ranked in the world’s top 20, Group B contained players ranked 21 to 75 in the world, while Group C contained players ranked outside the world’s top 75. This meant that there were nine different types of performance; A v A, A v B, A v C, B v A, B v B, B v C, C v A, C v B and C v C. This technique was not only used to evaluate individual performances accounting for the quality of the opponent, but it also allowed trends in performances within tournaments to be monitored. Performance indicator values might decrease during successive rounds of a tournament simply because the quality of opponent increases as a player progresses from the first round to the final. The use of norms based on the quality of the player and the opponent in each round allows a more meaningful comparison to be made between performances. The technique is not used to profile performers’ typical performances, however, and O’Donoghue’s (2005) technique using unified norms would be recommended for this purpose, while separate norms would be used to evaluate individual performances.

Regression-based interpretation of performance indicators

The technique

The technique of O’Donoghue et al. (2008) interprets performances using norms for the particular type of match being evaluated. Most importantly, the technique uses different norms depending on the quality or rankings of the performers involved. As noted, the technique has been applied in British Superleague netball between 2005 and 2008 where there was justification for assuming two broad strengths of team (O’Donoghue et al., 2008); there were four teams at the upper half of the league with a noticeable gap to the four teams in the lower half of the league. Cullinane and O’Donoghue (2011) investigated performances of a semi-professional rugby league team and noticed that performance indicator values changed gradually.
as opposition quality increased or decreased, rather than producing a 'plateauing' effect assumed by O’Donoghue et al. (2008). An important disadvantage of O’Donoghue’s (2008) approach in tennis is that the same decile norms are used to represent performances against any opponent ranked between 21 and 75 in the world. This risks an evaluation overestimating a performance against the world number 75 and underestimating a performance against the world number 21.

This issue motivated Cullinane (2011) to develop a profiling technique that used a finer-grain approach to addressing opposition quality. This technique is made up of the following steps:

1. Determine an indicator of performer quality – for example, the league position of a team or a world ranking of an individual performer.
2. Use recent and relevant performance data to produce models for performance indicators in terms of relative quality of the performers that contest matches. The relative quality of the match is a function of the difference between the quality indicators for the performers involved.
3. The performances used to produce the models of performance indicators are also used to determine the spread of performance indicator values about the expected performances.
4. Use these models to interpret performance indicator values in future performances. This is done by comparing the observed performance indicator values with the expected values determined using the models. A residual value is the difference between the observed and the expected value for a performance indicator. The residual value can be interpreted using the known spread of historical values, giving a percentage evaluation score that addresses opposition quality.

Readers should note the use of the plural (models instead of model) in the steps above. This is because the use of a regression equation and the known distribution of residuals alone do not produce a performance profile. When dealing with a single performance indicator, the technique simply provides a means of interpreting that individual performance indicator addressing opposition quality. It is when the technique is applied to multiple performance indicators producing percentage evaluation scores for the full set of relevant performance indicators that a performance profile is produced.

This technique has several advantages over O’Donoghue et al.’s (2008) technique that assumed broad groupings of performers with respect to quality. First, smoother and more realistic relationships between performance indicators and relative quality are represented. Second, the technique is a flexible and general technique that can be used with different types of relationship between performance indicators and relative quality. For example, curvilinear models can be supported as well as linear models. Third, the residual values do not have to be normally distributed or homogeneous. Where other distributions are evidenced from the previous case data used to create the models, these other distributions can be applied when interpreting performance indicator values. Fourth, the percentage evaluation score is not a broad decile or quartile band that a performance is judged to fit within, but is on a continuous scale. The percentage evaluation score represents the percentage of matches between performers of the given qualities where the performance indicator value would be expected to be lower than the value observed.

This chapter discusses how the technique can be used to produce profiles for individual performances as well as for performers. There is another use of the technique, which is to evaluate trends in performance addressing opposition quality (O’Donoghue and Cullinane, 2011).
A performance profile

The technique should only be used where there is evidence of a relationship between the relative quality of the performers and the performance indicators. Of the 13 performance indicators used in the Australian and US Open men’s singles tennis data, the percentage of points won when the first serve was in (S1) and the percentage of points won when a second serve was required (S2) had a positive linear relationship with relative quality. Relative quality, RQ, was defined as the difference between the quality ratings, RX and RY, of the two players, X and Y, contesting a match. The 52-week world ranking, RankX, of player X was transformed into a quality rating, RX, using the method described by Klaassen and Magnus (2001), as shown in equation (11.1).

\[ RX = 8 - \log_2(Rank_X) \]  

RX is an estimate of the round in the tournament a player could be expected to reach based on his ranking for singles. For example, the world number 1 would be expected to win the tournament (RX = 8), while the world number 2 would be expected to reach the final (RX = 7), the world number 4 would be expected to reach the semi-final (RX = 6), the world number 128 would be expected to reach the first round (RX = 1) and the world number 512 would be expected to reach the penultimate qualifying round (RX = -1).

Given that one player’s serving performance is another player’s receiving performance, the percentage of receiving points won when the opponent’s first serve was in (R1) and the percentage of receiving points won when the opponent required a second serve were also correlated with relative quality. Once regression models for the expected values of S1, S2, R1 and R2 in terms of RQ are created, it is possible to evaluate a performance. This is done using the following steps:

1. Determine the expected value for a performance indicator based on the relative quality of the players involved in the match. For example, the model of S1 is \( S1 = 1.723RQ + 70.566 \).
2. Determine the residual value, which is the difference between the observed and expected values for the performance indicator.
3. Divide this residual by the standard deviation of the residuals in the data used to create the model to give a z-score (if the residuals are normally distributed). For example, the standard deviation for the residuals of S1 in men’s singles at the Australian and US Open’s is 8.184.
4. Using the standard normal distribution (or an alternative distribution if necessary), determine the area of the probability distribution for the residuals for z-scores less than that calculated in step 3.
5. Multiply the probability determined in step 4 by 100 to achieve a percentage evaluation score.

The percentage evaluation score addresses the relative quality of the two players, thus allowing relative performance to be assessed. An absolute assessment is still possible if the original performance indicators are used instead of the relative evaluation scores. A crude evaluation could use the average of the four performance indicators to represent absolute performance and the mean of the four percentage evaluation scores to represent relative quality. Consider the sequence of performances for Novak Djokovic shown in Table 11.2. The best performance
<table>
<thead>
<tr>
<th>Opponent name</th>
<th>S1 Rank</th>
<th>Value</th>
<th>%ES Value</th>
<th>S2 Rank</th>
<th>Value</th>
<th>%ES Value</th>
<th>R1 Rank</th>
<th>Value</th>
<th>%ES Value</th>
<th>R2 Rank</th>
<th>Value</th>
<th>%ES Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gimeno Traver</td>
<td>74</td>
<td>75.8</td>
<td>37.0</td>
<td>57.1</td>
<td>51.1</td>
<td>29.1</td>
<td>15.5</td>
<td>66.7</td>
<td>83.9</td>
<td></td>
<td></td>
<td></td>
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<td>Chiundelli</td>
<td>58</td>
<td>74.7</td>
<td>34.6</td>
<td>32.6</td>
<td>0.7</td>
<td>42.1</td>
<td>74.1</td>
<td>57.8</td>
<td>54.9</td>
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<td>103</td>
<td>73.3</td>
<td>23.1</td>
<td>45.2</td>
<td>9.9</td>
<td>60.6</td>
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<td>74.1</td>
<td>95.4</td>
<td></td>
<td></td>
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<tr>
<td>Kubot</td>
<td>86</td>
<td>80.4</td>
<td>57.2</td>
<td>69.6</td>
<td>90.0</td>
<td>31.9</td>
<td>23.7</td>
<td>69.0</td>
<td>88.4</td>
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<td>Tsonga</td>
<td>10</td>
<td>67.0</td>
<td>21.2</td>
<td>48.9</td>
<td>35.4</td>
<td>31.8</td>
<td>46.8</td>
<td>52.5</td>
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<td>50.0</td>
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<td>30.6</td>
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<td>31.3</td>
<td>26.3</td>
<td>50.0</td>
<td>25.6</td>
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<td>9.9</td>
<td>70.0</td>
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<td>35.8</td>
<td>38.0</td>
<td>45.8</td>
<td>10.5</td>
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<td></td>
</tr>
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<td>Fish</td>
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<td>78.8</td>
<td>66.3</td>
<td>45.8</td>
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<td>41.0</td>
<td>79.5</td>
<td>53.1</td>
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in absolute terms was against Berlocq, who was ranked 74 in the world. The worst performance in absolute terms was the four-set loss to Rafael Nadal in the final of the 2010 US Open. This absolute view of the performance indicators fails to account for Nadal being ranked world number 1 at the time. The worst performance in relative terms was against Troicki in an early round of the 2010 US Open. Although this was a win, the models of S1, S2, R1 and R2 suggest that Djokovic should have won more comfortably against this opponent. The best performance in relative terms was the victory over Andy Murray in the 2011 Australian Open final. In particular, winning 68.6 per cent of points where Murray had a second serve (R2) is a higher percentage than would be expected in 96.4 per cent of matches where the players involved had the same relative quality as Djokovic and Murray.

A performer profile

Although this technique was originally developed to address opposition quality when evaluating sports performance in individual matches, it also has an advantage when used to produce a profile of a performer. A disadvantage of O’Donoghue’s (2005) technique using quantiles is that two players’ typical profiles could be created using matches against different ranges of opposition. Players ranked in the world’s top four are more likely to play opponents ranked in the world’s top four than players ranked outside the world’s top 50 would be. This is because higher-ranked players tend to progress further in tournaments than lower-ranked players. This could lead to profiles for higher-ranked players being based on median values from matches against higher-ranked opponents than the average player would be expected to play.

The percentage evaluation scores for a series of matches used to create a profile have the advantage of addressing the quality of the opponent within each match. This means that a typical performance profile based on evaluation scores rather than the original performance indicator values will address the balance of opponents in the matches used.

Future work

The regression based technique of O’Donoghue and Cullinane (2011) is suitable for performance indicators whose values increase or decrease as relative quality increases. However, there are many performance indicators where optimal values are better – the percentage of points where the first serve is in during a tennis performance is an example. If this value is too low, the player will have too many points emanating from a second serve, which has been shown to be less effective than when the first serve is in (O’Donoghue and Ingram, 2001). If the percentage of points where the first serve is in is too high, it could be because the serve is easier to return. For example, the serve is in because it is not placed close enough to the lines or because it is not played fast enough. Research is needed to develop a means of identifying optimal values of such performance indicators and a means of evaluating these, such that optimal values are graded better than values that are too high or too low.

A second area for future research is to weight recent performances more highly than earlier performances when producing performer profiles based on multiple performances. Mosteller (1979) proposed weighting the most recent matches within a profile more heavily than earlier matches with matches eventually being excluded from the data used to produce the profile when they were deemed to be no longer current. This could be a potential extension to all of the performance profiling techniques described in this chapter.
Concluding remarks

This chapter has described four profiling techniques used in performance analysis of sport. What all four have in common is that the profiles contain a set of performance indicators that together characterise performance in the given sport. James et al. (2005) used 95 per cent confidence intervals of the median. O’Donoghue (2005) used norms so that typical performances could be evaluated using quantiles in the same way that variables are evaluated in other disciplines. O’Donoghue et al. (2008) addressed opposition quality by using separate norms for different types of matches. This can be considered a coarse-grain approach because it is assumed that there are broad classes of matches. The most recent profiling technique is that of Cullinane and O’Donoghue (2011), which applies a more fine-grain approach, assuming gradual change in expected performance indicator values as the quality of opposition changes.

References


