Bayesian networks for unbiased assessment of referee bias in Association Football

THIS IS A PRE-PUBLICATION DRAFT OF THE FOLLOWING CITATION:

Constantinou, A. C., Fenton, N. E., & Pollock, L. J. H. (2014). Bayesian networks for unbiased assessment of referee bias in Association Football. *Journal of Psychology of Sport and Exercise, Vol. 15, 5: 538-547*.

DOI: doi:10.1016/j.psychsport.2014.05.009
CONTACT: Dr. Anthony Constantinou, anthony@constantinou.info, a.constantinou@qmul.ac.uk

Abstract

Objectives: To assess referee bias with respect to fouls and penalty kicks awarded by taking explanatory factors into consideration.

Design: We present a novel Bayesian network model for assessing referee bias with respect to fouls and penalty kicks awarded. The model is applied to the 2011-12 English Premier League season.

Method: Unlike previous studies, the model takes into consideration explanatory factors which, if ignored, can lead to biased assessments of referee bias. For example, a team may be awarded more penalties simply because it attacks more, not because referees are biased in its favour. Hence, we incorporate causal factors such as possession, time spent in the opposition penalty box, etc. prior to estimating the degree of penalty kicks bias.

Results: We found fairly strong referee bias, based on penalty kicks awarded, in favour of certain teams when playing at home. Specifically, the two teams (Manchester City and Manchester United) who finished first and second appear to have benefited from bias that cannot be fully justified by the explanatory factors. Conversely Arsenal, a team of similar popularity and wealth and who finished third, benefited least of all 20 teams from referee bias at home with respect to penalty kicks awarded.

Conclusions: Among our conclusions are that, in contrast to many previous studies, being the home team does not in itself result in positive referee bias. More importantly, the model is able to explain significant discrepancies of penalty kicks bias into non-significant after accounting for the explanatory factors.

Keywords: causal modelling, crowd effect, home advantage, officiating bias, soccer

Introduction

The notion that referees in Association Football (hereafter referred to simply as *football*) are biased towards certain teams or in certain contexts is widely accepted by football pundits and supporters. In fact, whether or not such bias exists is an area of increasing interest that attracts the attention of researchers from the domains of sport science, psychology, statistics and computer science.

Irrespective of the true underlying causes, there is no doubt that 'playing at home' has a significant impact on a team's success. This home advantage effect has been extensively studied (Courneya & Carron, 1992; Nevill & Holder, 1999; Hirotsu & Wright, 2003; Pollard & Pollard, 2005; Pollard, 1986; 2006; Poulter, 2009; Anders & Rotthoff, 2012; Constantinou & Fenton, 2013). Numerous explanatory factors have been proposed for home advantage. The crowd effect is normally suggested as one of the most important factors (Agnew & Carron, 1994; Nevill et al., 1996; Nevill et al., 1999; 2002; Downward & Jones, 2007; Dohmen, 2008; Goumas, 2012) and is said to occur to a greater extent in leagues in which home crowds are more hostile and vociferous (Anders & Rotthoff, 2012). Other proposed factors include the travelling effect (Clarke & Norman, 1995), the familiarity with the playing grounds (Neave & Wolfson, 2003; Pollard, 2006), as well as referees themselves who are said to favour home teams on the basis of penalty kicks, free kicks, yellow/red cards and/or extra time data (Nevill et al., 1996; Nevill et al., 1999; 2002; Sutter & Kocher, 2004; Boyko et al., 2007; Downward & Jones, 2007; Dawson et al., 2007; Dohmen, 2008; Buraimo et al., 2010; Goumas, 2012). However, the degree of influence of referee decisions relative to the overall home advantage effect has not been extensively studied.

It is apparent that the literature tends to indicate with strong belief that referee decisions favour the home team. However, some researchers (Page & Page, 2010) have questioned this outcome and expressed their uncertainty as "*it could be the case that these biases do not manifest themselves into significant differences in terms of the overall performance of a team*" (Page & Page, 2010); the increased number of fouls, yellow cards, red cards, penalties and so on in favour of the home team might simply be the result of the home team performing better than the away team. For example, if the home team is in control of the ball (possession) more often than not, then we would expect it to be awarded more fouls and penalties, and less yellow and red cards relative to the opponent, on the basis that its control of possession will lead to it being on the receiving end of more tackles. We should also expect a higher proportion of these to be committed nearer to the opponent's goal, as greater possession also tends to correspond to a marked territorial advantage. We agree that the kind of explanatory causal factors proposed in (Page & Page, 2010) must be incorporated into any study of referee bias.

Hence, in this paper we present a novel Bayesian network (BN) model developed for referee bias analysis in football. It is the most comprehensive attempt to date to include within-game explanatory variables in order to justify the observed discrepancies between fouls and penalty kicks awarded between adversaries prior to formulating beliefs about referee bias. Although previous attempts have been made to control within-game events such as shots, fouls and corners (Dohmen, 2008; Goumas, 2012), this paper integrates a number of important additional variables which are required for formulating a causal network model, specifically for penalty kicks awarded.

The paper is organised as follows: Section 2 describes the BN model, Section 3 discusses the results and Section 4 provides our concluding remarks.

The model

In this section we describe the BN model which was developed using the AgenaRisk BN tool (Agena Ltd., 2013). The tool was chosen because of its ability to properly incorporate continuous variables, without any constraint (like Normality), and without the need for static discretisation. This is achieved through its dynamic discretisation algorithm (Neil et al., 2010). Details about the role of qualitative judgments and how inference is done are provided in (Fenton et al., 2007; Neil et al., 2010; Fenton & Neil, 2012).

The data used to inform priors and provide observations for each of the teams is available online at (WhoScored?.com, 2012), although the data for number of penalties awarded was manually recorded by a member of the research team from bbc.co.uk/football. However, the data is limited in the sense that, instead of having the value for each explanatory factor for each team in each match, we only have the averaged values for a set of match instances (namely match instances at home, away, and overall). With this limitation in place we have to make distributional assumptions based on expert judgment.

The data limitation also affects our ability in performing accurate simulation for estimating penalty kicks awarded. Specifically, for a proper simulation we want to know, for example, the percentage of time spent in the opposition penalty box (while in possession of the ball) relative to the overall percentage of possession for each individual match, rather than the average values over a number of match instances. Since we have a known average rate, distributional assumptions such as the *~Poisson distribution*, which expresses the probability of a given number of events occurring in a fixed interval of time, help us in addressing these issues by also keeping the model simple (more details in the subsections that follow). The drawback is that uncertainty is increased, since we are estimating those values for each match.

The model is constructed on the basis of two components as illustrated by the model topology in Figure 1. Component 1 (described in Section 2.1) measures the referee bias over all fouls awarded, while Component 2 (described in Section 2.2) measures the referee bias over fouls awarded within the opposition penalty box (effectively penalty kicks). All the technical information required for developing the model (by following the model topology presented in Figure 1) are provided in Table B.1.

The model is used to assess the referee bias for each case at home, away, and overall. While it is possible that there is some dependency between the two biases, our analysis assumes that they are independent; implying that the bias for penalty kicks awarded is only measured based on penalty kicks predicted and observed, and the same applies for the free kicks bias.

Component 1

This component simply assumes that the fouls awarded in a game are a consequence of a team's ability with respect to the following attributes (each corresponding to a node in the model):

1. *Possession*: percentage of time the team is in control of the ball (we assume *Truncated ~Normal* distribution);
2. *Pass accuracy*: the percentage of successful passes (i.e. those that reach a team mate, and we assume *Truncated ~Normal* distribution);
3. *Aerial duels*: the percentage of aerial duels won (we assume *Truncated ~Normal* distribution);
4. *Dribbles*: the average number of times, per match instance, a player manoeuvres the ball around a player of the opposing team (we assume ~*Poisson* distribution);
5. *Interceptions*: the average number of times, per match instance, a player intercepts a pass made by a player of the opposing team (we assume ~*Poisson* distribution).

Accordingly, we use the above five observable variables as predictors, in a naive Bayesian classification framework, for the latent variable *True fouls awarded* (predicted average per match instance) for a team at the specified ground (we assume ~*Poisson* distribution). Subsequently, the referee bias is simply inferred by measuring the discrepancy[1] in distributions between *predicted* (*True fouls awarded* node) and observed (*Fouls awarded* node) fouls awarded, with the bias level set to $\geq 10\%$ in terms of variability between the two distributions.

Figure A.1 presents a BN example of this component with the observations of QPR and Arsenal as inputs when playing at away grounds. The comparison in Figure A.1 shows that even though Arsenal generated superior statistics for all of the five explanatory parameters, they were still awarded 1.1 fouls less per match instance compared to QPR. As a result, the *Referee bias* distribution provides weak evidence of *Bias For* for QPR and *Bias Against* for Arsenal.

Component 2

The second component represents the key process of determining referee bias given penalties awarded. Unlike the first component which follows the process of a naive Bayes classifier, this component is a causal Bayesian network. The steps can be enumerated as follows:

1. We convert the possession rate into time spent (in minutes) holding the ball, and we use the positional statistics of *Action Zones*[2] and *Shot Zones*[3] to estimate the time spent respectively at a) opposition third, and subsequently at b) opposition penalty box. Essentially, we are only interested in (b), since there is where the penalties are awarded.

2. We then measure the probability of being awarded a foul for each minute spent while in possession of the ball, at any part of the pitch, given the following two parameters:

[1] While the common practise is to let the *true* value be the parent of the *observed* value, we chose to model this relationship in an inverse manner. This is due to the naive Bayesian assessment performed; i.e. if we had followed the common practise then the *true* value would had been predicted (up to a degree, depending on how the *bias* node is defined) given the *observed* value (as it happens with all of the other factors in the naive Bayes framework). The way we chose to model this (i.e. not following the common causal practise) certainly keeps the *true* value constant, and the discrepancy between *true* and *observed* values is fully explained in the *bias* node.

[2] The positional statistical information regarding action zones (i.e. where the ball is played) is distributed in *Own Third*, *Middle* and *Opposition Third*. This information is used to estimate the time spent at each third of the pitch, while in possession of the ball.

[3] The positional statistical information regarding shot zones (i.e. where do the shots come from) is distributed in *6 Yards Box*, *18 Yards Box*, and *Outside of Box*. This information is used to estimate time spent at opposition penalty box while in possession of the ball (both the *6 Yards Box* and the *18 Yards Box* information contribute to time spent at opposition penalty box).

a) the rate of observed fouls awarded from Component 1, and b) time spent holding the ball (from step 1 above). Specifically, *p(fouled per minute)* follows a ~*Beta* distribution with (a) and ((b)-(a)), as defined above, serving as the respective *alpha* and *beta* hyperparameters for the ~*Beta* distribution.

3. Similar to step 2, we measure the probability of being awarded a foul for each minute spent while in possession of the ball in the opposition penalty box given the following two parameters: a) number of penalties awarded, and b) time spent holding the ball while in the opposition penalty box (from step 1b above). For the analysis we assume that fouls awarded within the penalty box are penalty kicks (there are examples of indirect free kicks in the penalty area but these are rare). Inference for *p(fouled per minute in the penalty box)* is achieved using the *Beta-Binomial* approach. Specifically, the ~*Beta* distribution *p(fouled per minute in the penalty box)* serves as conjugate distribution of the ~*Binomial* distribution *Penalties awarded*, formulating a compound distribution such that the *p* parameter of the ~*Binomial* distribution is being randomly drawn from the ~*Beta* distribution[4]. The parameter *n* of the ~*Binomial* distribution is the ~*Poisson* distribution *Minutes at opposition penalty box*. Since we are modelling the total number of penalties for match instances at home, away, or overall, the ~*Binomial* distribution assumes that parameter *n* is multiplied by 19 (home/away) or 38 (season overall).

After steps 2 and 3, we can compare the two inferred probability distributions and measure how the probability of *fouls awarded per minute* varies with *fouls awarded per minute while in opposition penalty box*. In doing so, the model takes account of the extra sensitivity of fouls committed inside the penalty area since a penalty kick awarded is very often decisive[5] on the final outcome. As a result, for this analysis we take into consideration the following widely accepted observations that a) when a player is defending in his own penalty box he is extra careful not to commit a foul, and b) the referee is also extra careful when awarding such fouls. Accordingly, the next step is:

[4] Therefore, the *p* parameter *p(fouled per minute in the penalty box)* is dependent on the *n* parameter *Minutes at opposition penalty box* given the Binomial distribution *penalties awarded* (even though in the model topology the *Minutes at opposition penalty box* does not appear to serve as the parent for *p(fouled per minute in the penalty box)*).

[5] In particular, during our period of analysis, 72% of penalties awarded were converted by the attacking team, while a single goal would have been sufficient to decisively alter the balance of the overall result in 61% of matches played.

4. To let the model explain the discrepancies between the two inferred probability distributions (from steps 2 and 3) into the following two explanatory variables: 1) *Carefulness by defenders*, and 2) *Carefulness by referees.* Since we are only interested in inferring the referee bias, we assume that the level of carefulness by defenders is fixed and identical for all teams (the assumption we use is 'double careful'). The model then explains the residual variation in node *Carefulness by referees;* effectively referee bias (i.e. the less careful referees are the more penalties a team is awarded and thus, the higher the positive referee bias). In particular, we assume that if referees are more (respectively less) likely - all factors being equal - to award penalties to a particular team than to the other teams, then there is a degree of positive (respectively negative) bias towards that team.

Results and discussion

Using data from the full English Premier League (EPL) season 2011-12, we have compared a) the referee carefulness given fouls awarded between teams (Component 1), b) the referee carefulness given penalties awarded between teams (Component 2), and c) the association of (a) and (b) inferences with crowd attendance and crowd density for each team.

Table C.1. presents the relative percentage increase in performance, for each of the explanatory variables, a team gained when playing at home relative to the away match performances. As expected, the average team demonstrated increases in possession (5.94%), pass accuracy (0.94%), aerial duels won (4.57%), successful dribbles (13.24%) and fouls awarded (3.04%). When it comes to interception, the average team demonstrated a decrease of 1.34%, although this is not surprising since in order to be able to intercept the ball the opponent has to be in possession. However, the variability between teams for this particular factor is very high.

The referee bias (or carefulness), for both fouls and penalties awarded, is inferred using *Ranked Truncated ~Normal* distributions (as specified in Table B.1) with lower and upper bounds of 0 and 1 respectively. When the distribution mass falls closer to 0, this indicates a positive referee bias (*Bias For*) and vice versa for a negative referee bias (*Bias Against*). Tables D.1 (free kicks bias) and D.2 (penalty kicks bias) present the summary statistics for the inferred biases, for each team and specified ground, ranked by distribution mean.

However, we want to know what these bias differences between teams really mean. To address this, we perform Bayesian hypothesis testing between inferred distribution biases. Figure 2 presents two examples that illustrate how the belief for the hypothesis "*more positive/negative referee bias*", for penalties awarded, is inferred based on the discrepancies between the two inferred skewed distribution biases presented. Specifically, the examples 1 and 2 compare the inferred penalties awarded bias for Manchester United against Arsenal and Manchester City respectively, when playing at home. A hypothesis of 50% for each outcome indicates no bias between the two teams under assessment. Example 1 shows that the probability for Manchester United receiving more positive referee bias, for penalties awarded at home, compared to Arsenal is 86.09% which indicates that there is a good chance for some bias. On the other hand, the respective probability against Manchester City (i.e. example 2) is 49.39%; implying that there is no difference between inferred distribution biases for the two Manchester clubs.

Tables 1 (free kicks bias) and 2 (penalty kicks bias) present these hypothesised probabilities, both before (i.e. prior hypothesis H_{PR}) and after (i.e. posterior hypothesis H_{PO}) the explanatory factors are taken into consideration, along with the average number of fouls awarded per match, at the specified grounds, for each of the teams. We discuss the results on free kicks and penalty kicks biases in greater detail in the respective subsections below.

Referee bias given fouls awarded (Component 1)

Table 1 presents the teams ranked by highest H_{PO} for *more positive bias for free kicks awarded*, relative to the team with the highest negative respective bias (i.e. the team ranked last in each of the table sections). From a quick look at the table we can observe that none of the cases (both for H_{PO} and H_{PR}) indicate bias that can be labelled as statistically significant (i.e. a bias belief of 95% or more) for free kicks awarded between teams and therefore, the bias discrepancies may well be explained simply by statistical fluctuations.

However, the model demonstrates that many of these fluctuations are explained by the explanatory factors, since the H_{PO} beliefs are closer to the unbiased judgment of 50% than most of the respective H_{PR} probabilities. As a result, the belief for significance in bias for free kicks awarded between teams is further diminished after considering the explanatory factors, making the fluctuations between biases not worth commenting on. Still it is interesting to observe, for example, that Arsenal who overall averaged 10.8 free kicks per match are still believed to have benefited less than Bolton who overall averaged just 9.3 free kicks per match.

Referee bias given penalties awarded (Component 2)

Table 2 presents the teams ranked by highest H_{PO} for *more positive bias for penalty kicks awarded*, relative to the team with the highest negative respective bias (i.e. the team ranked last in each of the table sections). For this assessment, we can immediately recognise that the discrepancies between biases is much stronger than the former. In fact, many H_{PR} beliefs between teams demonstrate highly significant discrepancies, which are subsequently revised into non-significant H_{PO} beliefs once the explanatory factors are considered by the model. However, in many cases the posterior bias beliefs remain strong (we discuss this in detail in the next Section) and are worth discussing. Specifically, Manchester United and Manchester City have been assessed as the two teams which received a fairly higher benefit by referee decisions when it comes to penalties awarded at home. In particular, Manchester United with 9 penalties awarded is ranked 1st in positive referee bias, generating an inferred H_{PO} belief of 86.09% (relative to Arsenal, and down from the H_{PR} belief of 99.46%), while Manchester City with 8 penalties awarded is ranked 2nd, generating an inferred H_{PO} of 86.03%. Conversely, neither of the teams appear to have received similar benefit when playing away from home. But, what makes this result particularly interesting is that these two teams were the only teams fighting for the EPL title and until the very last league match (i.e. each accumulated 89 league points; an impressive 19 points more than Arsenal who finished 3rd). Taking into consideration both home and away match instances, however, Manchester United is still ranked 1st in positive penalty kicks bias whereas Manchester City 4th and Arsenal last.

Referee bias and match attendance

Table 3 presents the teams ranked by highest H_{PO} at home grounds, with their respective average crowd attendance and average crowd density. Crowd density is the attendance size divided by home stadium attendance. It has been suggested in the literature as a significant predictor of home referee bias (e.g. Boyko et al., 2007; Goumas, 2012). In contrast to previous studies, our results do not demonstrate any strong positive relationship between crowd attendance (or crowd density) and positive referee bias. For example Arsenal, with the second largest average attendance as well as the second largest average crowd density, were ranked last in terms of positive referee bias for penalties awarded.

Concluding remarks and future research

Any credible attempt to determine referee bias in football matches must take account of causal explanatory factors. We have presented a novel Bayesian network model for this purpose. The model enables us to account for the observed discrepancies in fouls and penalty kicks awarded between teams by taking into consideration causal factors such as possession, time spent in the opposition penalty box while in control of the ball, pass accuracy, the ability to win aerial duels in the air, the ability to dribble the ball and the ability to intercept the opponent's pass.

Using the data for the 2011-12 EPL season the results demonstrate that the model successfully explains much of the bias. Specifically, many of the prior beliefs about referee bias for penalties awarded deviated significantly between teams, but the revised posterior beliefs (which accounted for the relevant explanatory factors) demonstrate no statistical significance in deviations of referee bias. However, we are not convinced with the notion that referee bias in football has to deviate significantly between teams for us to speculate that referee bias might still be present. It may be incorrect to treat these posterior beliefs as being uninteresting on the basis that the model explains the discrepancies sufficiently well so that they are labelled as non-significant in statistical terms.

The posterior beliefs, with respect to penalties awarded, indicate that there ***was*** still a fairly strong referee bias in favour of Manchester United and Manchester City in their home games compared to most of the other teams (i.e. these hypotheses are valid with respective probabilities of 86.09% and 86.03% when the teams are assessed against Arsenal; the team who benefited the least from referee decisions when it comes to penalty kicks awarded). However, this did not extend to away games (Manchester City, in fact benefited less than any other team away from home) nor to free kicks generally. The two Manchester clubs were, however, the only serious title contenders in an extremely close title-race. While popular lay theories suggest that referees have a tendency to favour elite clubs in general and Manchester United in particular, at their home stadiums, it is possible that the combination of home advantage and being a title-favourite team (which Manchester United have been since the Premier League inception) in a close-title race is what is more predictive of positive referee bias for penalty kicks awarded. To test such hypothesis properly would require applying the model over multiple seasons.

The results presented in this paper, in terms of bias for penalties awarded, should be interpreted with care on the basis that a) the extra carefulness by defenders, while defending within the penalty box, is modelled sub-optimally (i.e. subjectively, by assuming double carefulness for all teams) due to absence of relevant hard evidence, and more importantly b) the *foul quality*, for fouls awarded within the penalty box (i.e. penalties awarded), is not taken into consideration. No relevant (official) data exists that provides information on *foul quality* and this might be due to the fact that *foul quality* is very difficult to judge for consensus (e.g. it is very common for even 'unbiased' experts to disagree when it comes to judging penalties awarded). Both of these aspects could further explain the residual bias in penalties awarded.

Other important results from applying our model to the 2011-12 EPL season run counter to the prevailing wisdom. For example, much of the previous literature suggests that the influence of home crowd is a leading factor in explaining the observed discrepancies of officiating behaviour between home and away teams (Nevill et al., 1996; Nevill et al., 1999; 2002; Downward & Jones, 2007; Dohmen, 2008; Buraimo et al., 2010; Goumas, 2012). However, we found that the home crowd alone is not associated with positive referee bias. It should be acknowledged that there is some evidence that refereeing bias varies from league to league in conjunction with crowd hostility (Anders & Rotthoff, 2012), and caution should therefore be exercised in generalising the findings of the present study to all of world football prior to the application of BN modelling to other major leagues. In order to formulate such a conclusion, one has not only to understand the degree of impact of home crowd on home advantage, but also to measure home advantage for individual teams before assessing referee bias. After all, crowd attendance and crowd density tend to vary in conjunction with team performance (i.e. teams which perform best tend to have a large fan base and thus larger stadiums). In (Constantinou & Fenton, 2013) the results show how home advantage can differ considerably between teams of the EPL, whereas (Clarke & Norman, 1995) reported that in many cases a team can even develop a negative home advantage. However, this cannot be true for every football league and season; i.e. in (Heuer & Rubner, 2009) it has been shown for the German Bundesliga that the home advantage is basically identical for all teams.

It is also important to note that neither crowd size nor crowd density is necessarily correlated with crowd noise in the intuitive manner that might be expected. No published peer-reviewed study on noise-levels within the EPL stadiums exists, but 2008 and 2011 attempts to measure their decibel levels by Sky Sports[6] and fanchants.com[7] suggest little or no correlation, with several clubs with smaller attendances and lower crowd densities ranking above many of the elite teams in both studies. Factors such as differing stadium acoustics, fan demographics, and the varying levels of organisation and coordination of the most vocal elements of the home support likely play a part in this. It is also important to remember that in the EPL, a league with a high ratio of visiting supporters, there is often a very substantial level of vocal support for the away team also present at almost all fixtures, thus partly confounding the notion that larger crowd generating higher noise levels necessarily means greater vocal support for the home team.

Our results lead us to conclude that Page and Page (2010) were correct to question the effect of the home crowd in the absence of team performance. It appears that the explanatory variables taken into consideration by our model (which represent different aspects of team performance) have explained most of the biases when it comes to free kicks and penalty kicks awarded between home and away teams; crowd attendance and crowd density are not related with positive referee bias.

Whether or not there are underlying factors not yet accounted for in our model (such as 'being title contenders', having 'great wealth' or even the possibility that referees secretly support these clubs), as well as the relevance of those factors with other aspects of referee bias (i.e. yellow and red card), is a matter for future research. If information such as possession and positional statistics in combination with the ability to dribble, win aerial duels and so on, also becomes available for individual match instances (rather than overall as it was in our case) then we will be able to accurately determine referee bias with much higher confidence. This will be achieved by also looking at how certain teams might have further benefited by *negative* referee bias for their opponents in a match between them (i.e. the possibility that the two Manchester clubs benefited not only from penalties awarded, but also from penalties not awarded - i.e. *Bias Against* - for their opponents when playing against them). We anticipate that our model now lays out a coherent and rational strategy for conducting such research.

[6] http://www.bbc.co.uk/dna/606/A42697579 and http://www.stoke.vitalfootball.co.uk/article.asp?a=129620
[7] http://epltalk.com/2011/05/13/top-20-loudest-football-grounds-in-premier-league/

Tables

Table 1. Teams ranked by highest posterior belief H_{PO} for *more positive bias for fouls awarded* relative to the team with the highest negative respective bias.

HOME					AWAY					OVERALL				
R	TEAM	H_{PO}	F	H_{PR}	R	TEAM	H_{PO}	F	H_{PR}	R	TEAM	H_{PO}	F	H_{PR}
1	QPR	62.97	12.5	78.56	1	QPR	57.66	11	55.26	1	QPR	58.15	11.7	61.94
2	Newcastle	61.79	12.2	76.73	2	Wigan	56.47	11.7	61.09	2	Newcastle	57.35	11.4	59.50
3	Everton	59.91	11.3	70.60	3	Fulham	55.60	11.5	59.46	3	Wigan	56.76	11.1	56.99
4	Stoke	59.16	10.1	60.99	4	Stoke	55.48	10.6	51.79	4	Sunderland	56.20	10.1	48.25
5	Blackburn	59.11	10.2	61.85	5	Swansea	55.42	11.4	58.64	5	Fulham	56.06	11.1	56.99
6	Sunderland	59.09	10.7	65.98	6	Newcastle	55.10	10.5	50.91	6	Stoke	56.04	10.4	50.94
7	Swansea	58.31	11.4	71.33	7	Man City	54.31	11.3	57.80	7	Swansea	55.85	11.4	59.50
8	Wolves	58.07	10.6	65.18	8	Aston Villa	53.69	9.2	39.20	8	Wolves	55.38	10.3	50.05
9	West Brom	57.61	10.2	61.85	9	Sunderland	53.52	9.5	41.93	9	Everton	55.15	10.6	52.67
10	Wigan	57.04	10.5	64.36	10	Norwich	53.35	9.3	40.11	10	Blackburn	54.60	9.6	43.71
11	Arsenal	56.70	11.6	72.75	11	Man United	52.77	10.4	50.06	11	Chelsea	54.53	11	56.14
12	Bolton	56.59	9.7	57.45	12	Liverpool	52.77	10.7	52.66	12	Aston Villa	53.56	9.4	41.88
13	Fulham	56.57	10.8	66.78	13	Wolves	52.70	9.9	45.57	13	Bolton	53.37	9.3	40.96
14	Chelsea	56.22	11.3	70.60	14	Chelsea	52.63	10.6	51.79	14	Man United	53.08	10.2	49.15
15	Aston Villa	55.84	9.7	57.45	15	Everton	52.56	9.8	44.66	15	Liverpool	52.96	10.1	48.25
16	Tottenham	54.53	10.2	61.85	16	Tottenham	52.27	10.3	49.17	16	West Brom	52.86	9.4	41.88
17	Norwich	53.86	8.2	43.17	17	Blackburn	52.06	8.9	36.47	17	Tottenham	52.38	10.2	49.15
18	Man United	53.45	9.9	59.23	18	Bolton	50.45	8.9	36.47	18	Arsenal	52.34	10.8	54.42
19	Liverpool	53.29	9.5	55.62	19	West Brom	50.30	8.6	33.77	19	Norwich	51.30	8.7	35.49
20	Man City	50.00	8.4	50.00	20	Arsenal	50.00	9.9	50.00	20	Man City	50.00	9.8	45.53

Table 2. Teams ranked by highest posterior belief H_{PO} for *more positive bias for penalties awarded* relative to the team with the highest negative respective bias.

HOME					AWAY					OVERALL				
R	TEAM	H_{PO}	P	H_{PR}	R	TEAM	H_{PO}	P	H_{PR}	R	TEAM	H_{PO}	P	H_{PR}
1	Man United	86.09	9	99.46	1	Wigan	80.28	6	99.87	1	Man United	70.58	11	96.63
2	Man City	86.03	8	99.32	2	Bolton	78.90	5	99.66	2	Blackburn	68.95	7	81.55
3	Swansea	79.48	6	97.31	3	Tottenham	71.51	4	99.07	3	Bolton	65.46	7	81.55
4	Blackburn	77.55	6	97.31	4	West Brom	66.24	2	93.21	4	Man City	64.49	8	87.60
5	Stoke	67.57	5	95.54	5	Sunderland	66.08	2	93.21	5	Swansea	64.25	6	73.31
6	Fulham	64.54	3	84.04	6	Wolves	65.46	3	97.49	6	Wigan	64.23	7	81.55
7	Norwich	64.29	2	71.14	7	Arsenal	63.29	3	97.49	7	Stoke	58.05	6	73.31
8	QPR	63.17	3	84.04	8	Blackburn	63.01	1	81.57	8	Fulham	56.64	4	50.00
9	Chelsea	62.06	3	84.04	9	Newcastle	62.71	2	93.21	9	Liverpool	55.95	6	73.31
10	Liverpool	60.78	3	84.04	10	Liverpool	62.60	3	97.49	10	Tottenham	55.64	4	50.00
11	Bolton	60.71	2	71.14	11	Aston Villa	61.65	2	93.21	11	QPR	55.47	3	35.50
12	Everton	57.21	2	71.14	12	Chelsea	60.29	2	93.21	12	West Brom	55.17	3	35.50
13	Wigan	57.00	1	50.00	13	Everton	59.33	2	93.21	13	Chelsea	55.15	5	62.89
14	Aston Villa	56.65	1	50.00	14	Man United	59.30	2	93.21	14	Aston Villa	53.64	3	35.50
15	Newcastle	55.73	1	50.00	15	Fulham	59.23	1	81.57	15	Newcastle	53.52	3	35.50
16	West Brom	54.55	1	50.00	16	QPR	58.22	0	50.00	16	Norwich	53.43	2	20.91
17	Wolves	54.38	1	50.00	17	Stoke	56.87	1	81.57	17	Sunderland	53.36	2	20.91
18	Sunderland	54.30	0	18.42	18	Swansea	56.79	0	50.00	18	Wolves	53.23	4	50.00
19	Tottenham	52.01	0	18.42	19	Norwich	54.14	0	50.00	19	Everton	52.6	4	50.00
20	Arsenal	50.00	1	50.00	20	Man City	50.00	0	50.00	20	Arsenal	50.00	4	50.00

Table 3. Average home attendance and crowd density for all teams, ranked by home H_{PO}.

Ranked by H_{PO}	Team	Average crowd attendance	Average crowd density
1	Man United	75,387	99.06%
2	Man City	47,044	98.01%
3	Swansea	19,946	96.35%
4	Blackburn	22,551	70.12%
5	Stoke	27,225	95.92%
6	Fulham	25,293	98.50%
7	Norwich	26,605	97.74%
8	QPR	18,923	94.25%
9	Chelsea	41,477	99.14%
10	Liverpool	44,253	97.55%
11	Bolton	23,669	82.40%
12	Everton	33,228	81.90%
13	Wigan	18,633	74.46%
14	Aston Villa	33,873	79.17%
15	Newcastle	49,939	95.30%
16	West Brom	24,773	93.48%
17	Wolves	25,684	81.02%
18	Sunderland	39,095	79.78%
19	Tottenham	36,026	99.31%
20	Arsenal	60,000	99.28%

Figures

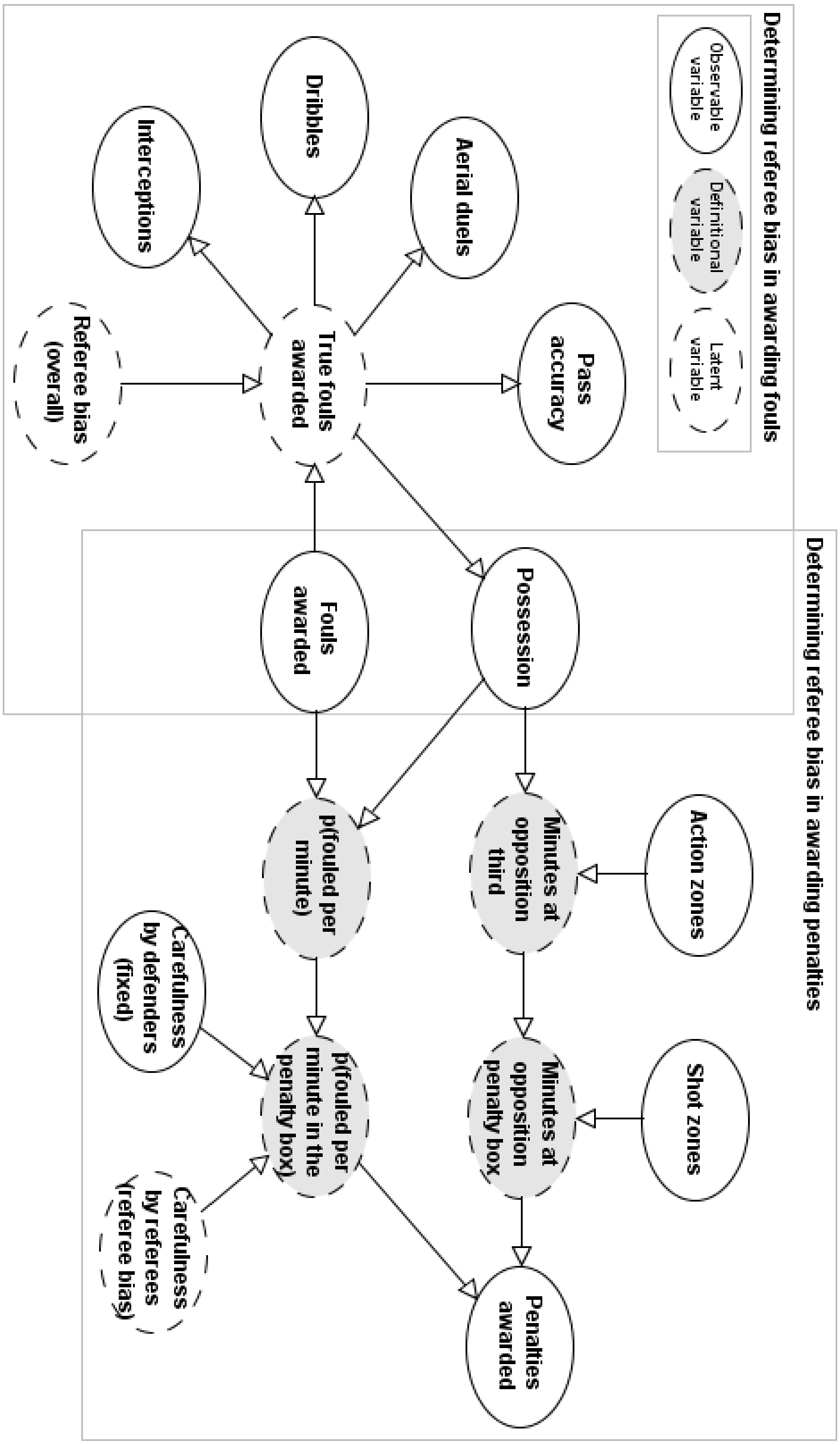

Figure 1. Bayesian network model topology; Components 1 and 2.

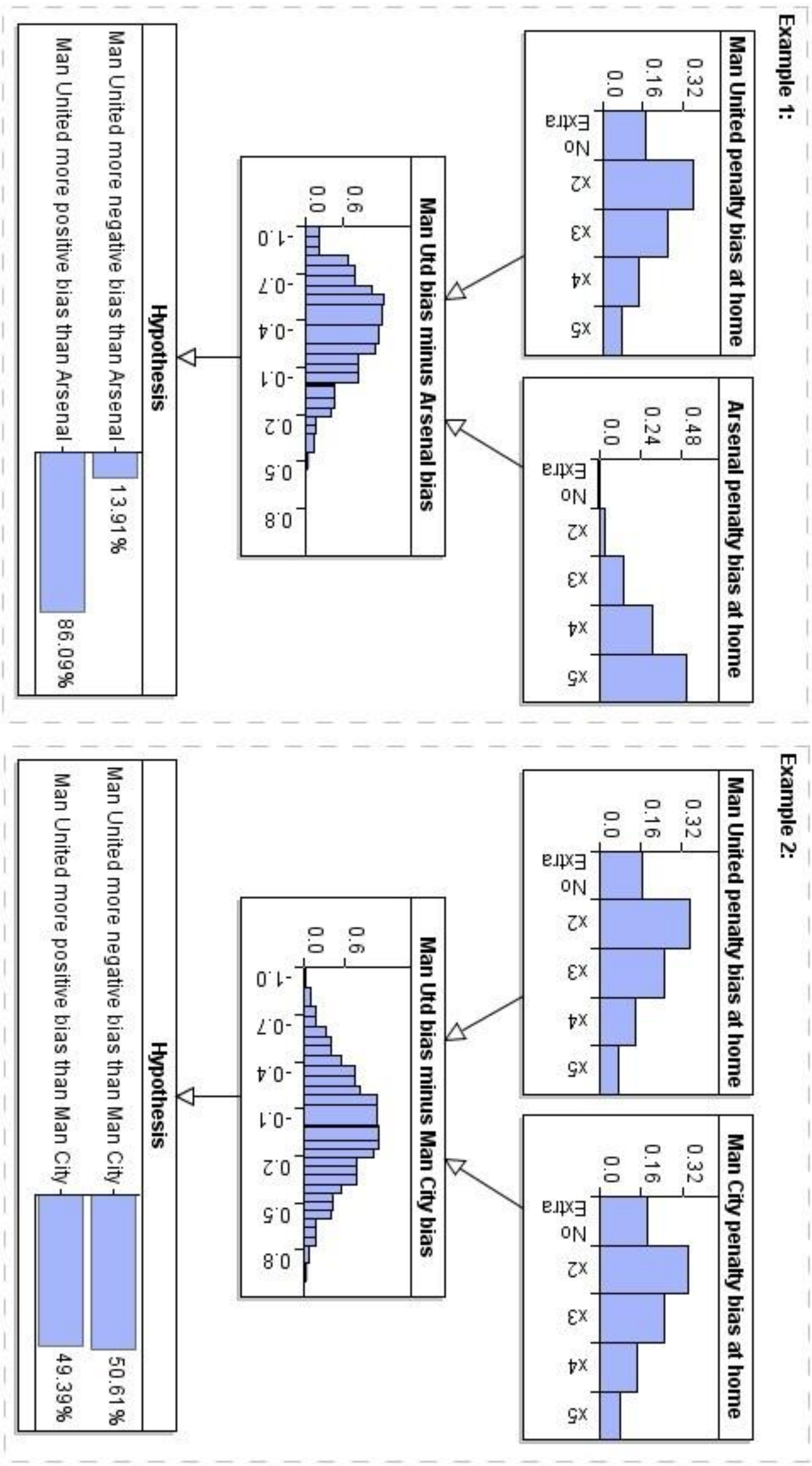

Figure 2. Examples of Bayesian hypothesis testing for inferred biases between teams.

Appendix A: BN model examples with scenarios

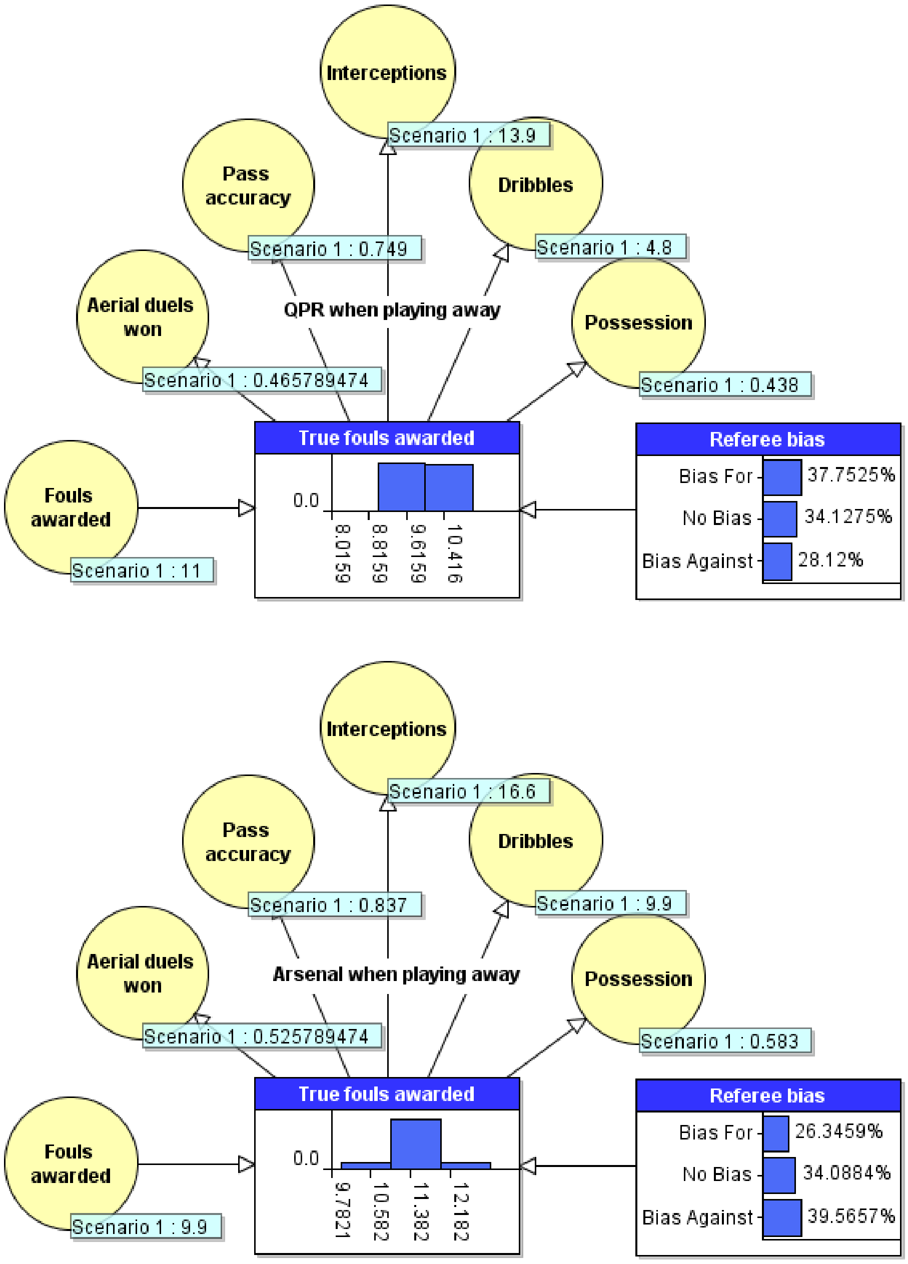

Figure A.1. Assessing referee bias given overall fouls awarded; a Component 1 example given observations of QPR and Arsenal when playing at away grounds.

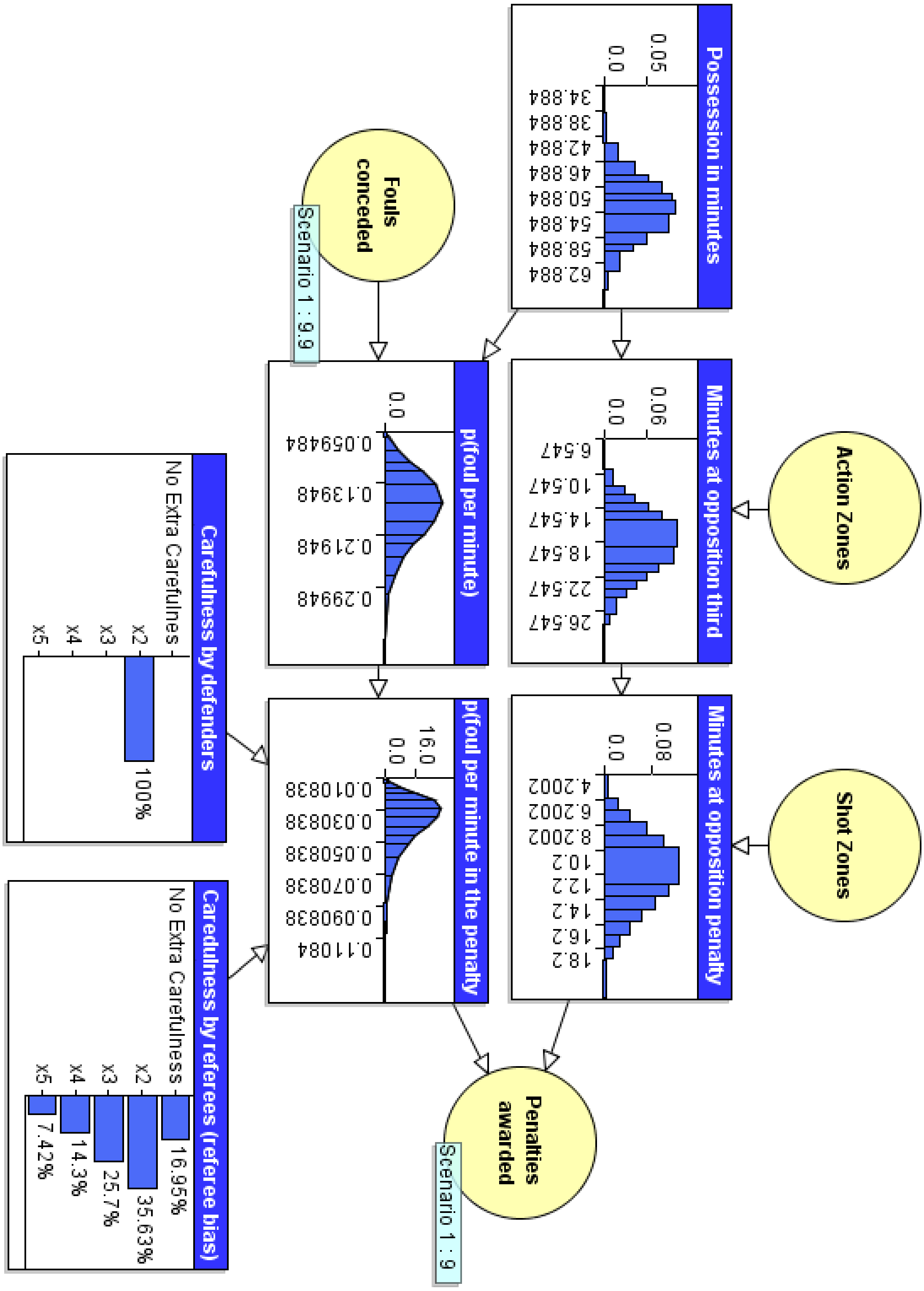

Figure A.2. Assessing referee bias given penalties awarded; a Component 2 example based on Manchester United home match data of the EPL season 2011-12.

Appendix B: Model description

Table B.1. Description of the BN variable nodes

Node name	Node ID	Node type	Observable/ Latent	Description
Possession	POS	$\sim\mathrm{TNormal}(\mu, \sigma^2, 0,1)$	Observable	where μ is the mean probability value observed over n match instances, and σ^2 is the variance associated with μ
Pass accuracy	PA	$\sim\mathrm{TNormal}(\mu, \sigma^2, 0,1)$	Observable	
Aerial duels	AD	$\sim\mathrm{TNormal}(\mu, \sigma^2, 0,1)$	Observable	
Dribbles	DR	$\sim\mathrm{Pois}(\lambda)$	Observable	where λ is the expected value over n match instances
Interceptions	INT	$\sim\mathrm{Pois}(\lambda)$	Observable	
Fouls Awarded	FA	$\sim\mathrm{Pois}(\lambda)$	Observable	
True fouls awarded	TFA	$\sim\mathrm{Pois}(\lambda)$	Latent	
Referee bias (overall)	RBO	Ranked $\sim\mathrm{TNormal}(\mu, \sigma^2, 0,1)$	Latent	with states '*Bias For*', '*No Bias*', and '*Bias Against*'. Assuming ignorant prior (uniformly distributed)
Action Zones	AZ	Labelled	Observable	with states '*Own third*', '*Middle third*', and '*Opposition third*'.
Shot Zones	SZ	Labelled	Observable	with states '*6 Yard Box*', '*18 Yard Box*', and '*Outside of Box*'.
Minutes at opposition third	MOT	$\sim\mathrm{Binomial}(n, p)$	Latent	$\mathrm{B}\begin{pmatrix}\mathrm{B}(90, \mathrm{POS}^{8}),\\ \mathrm{AZ}_{\mathrm{OppositionThird}}\end{pmatrix}$
Minutes at opposition penalty box	MOP	$\sim\mathrm{Binomial}(n, p)$	Latent	$\mathrm{B}\begin{pmatrix}\mathrm{MOT},\\ \mathrm{SZ}_{\mathrm{6YardBox+18YardBox}}\end{pmatrix}$
p(fouled per minute)	FM	$\sim\mathrm{Beta}(\alpha, \beta)$	Latent	$\mathrm{Beta}\begin{pmatrix}\mathrm{FA},\\ \mathrm{B}(90, \mathrm{POS}) - \mathrm{FA}\end{pmatrix}$
p(fouled per minute in the penalty box)	FMP	Arithmetic	Latent	$\frac{\mathrm{FM}}{(\mathrm{CD} \times \mathrm{CR})}$
Penalties awarded	PAW	$\sim\mathrm{Binomial}(n, p)$	Observable	$\mathrm{B}(\mathrm{MOP} \times \mathrm{g}, \mathrm{FMP})$; where $\mathrm{g} = 19$ represents the number of gameweeks at home/away grounds (and 38 for overall assessment)
Carefulness by defenders	CD	Ranked $\sim\mathrm{TNormal}(\mu, \sigma^2, 0,1)$	Latent	with states '*No Extra Carefulness*', '*x2*', '*x3*', '*x4*' and '*x5*'. Assuming ignorant prior (uniformly distributed).
Carefulness by referees (referee bias)	CR	Ranked $\sim\mathrm{TNormal}(\mu, \sigma^2, 0,1)$	Latent	with states '*No Extra Carefulness*', '*x2*', '*x3*', '*x4*' and '*x5*'. Assuming ignorant prior (uniformly distributed).

[8] Translated into minutes

Appendix C: Results

Table C.1. Relative percentage increase, of the value of the explanatory variables, for home match instances relative to away match instances.

EPL Position	Team	Possession	Pass accuracy	Aerial duels won	Dribbles	Interceptions	Fouls awarded
1	Man City	5.70%	3.07%	9.75%	8.54%	4.94%	-25.66%
2	Man United	8.36%	3.95%	-5.15%	33.78%	-0.66%	-4.81%
3	Arsenal	4.63%	2.15%	5.41%	-3.03%	-8.43%	17.17%
4	Tottenham	5.47%	3.24%	4.73%	5.95%	1.60%	-0.97%
5	Newcastle	15.67%	3.18%	5.93%	21.05%	-21.31%	16.19%
6	Chelsea	6.72%	2.50%	18.09%	30.77%	14.74%	6.60%
7	Everton	0.21%	2.22%	0.23%	61.76%	-0.61%	15.31%
8	Liverpool	6.57%	0.87%	3.70%	15.71%	-2.96%	-11.21%
9	Fulham	2.07%	-0.97%	7.29%	-3.08%	-7.39%	-6.09%
10	West Brom	5.44%	1.70%	-0.81%	3.23%	5.63%	18.60%
11	Swansea	6.08%	1.06%	6.05%	1.25%	-3.23%	0.00%
12	Norwich	3.74%	3.76%	7.39%	40.00%	-10.77%	-11.83%
13	Sunderland	5.59%	0.81%	-3.56%	18.37%	-18.52%	12.63%
14	Stoke	7.81%	-4.78%	-4.12%	2.78%	8.62%	-4.72%
15	Wigan	6.63%	1.13%	6.40%	4.05%	8.22%	-10.26%
16	Aston Villa	10.41%	2.50%	13.51%	-1.75%	-9.31%	5.43%
17	QPR	4.34%	-1.20%	-1.03%	43.75%	7.19%	13.64%
18	Bolton	5.33%	-1.38%	-8.82%	-35.14%	-9.90%	8.99%
19	Blackburn	6.23%	-2.59%	15.62%	-12.12%	18.50%	14.61%
20	Wolves	1.69%	-2.33%	10.78%	28.95%	-3.13%	7.07%
Average	-	5.94%	0.94%	4.57%	13.24%	-1.34%	3.04%

Appendix D: Summary statistics for referee bias

Table D.1. Summary statistics for free kicks bias.

HOME				AWAY				OVERALL			
TEAM	**Mean**	**Median**	**SD**	**TEAM**	**Mean**	**Median**	**SD**	**TEAM**	**Mean**	**Median**	**SD**
QPR	0.4514	0.4282	0.2668	QPR	0.4679	0.4530	0.2686	QPR	0.4704	0.4567	0.2688
Newcastle	0.4635	0.4465	0.2680	Wigan	0.4798	0.4706	0.2693	Newcastle	0.4784	0.4685	0.2693
Everton	0.4824	0.4744	0.2695	Fulham	0.4885	0.4832	0.2696	Wigan	0.4843	0.4772	0.2695
Stoke	0.4899	0.4853	0.2699	Stoke	0.4897	0.4850	0.2699	Sunderland	0.4899	0.4853	0.2699
Blackburn	0.4904	0.4860	0.2699	Swansea	0.4903	0.4859	0.2697	Fulham	0.4913	0.4874	0.2697
Sunderland	0.4906	0.4863	0.2699	Newcastle	0.4935	0.4905	0.2699	Stoke	0.4915	0.4876	0.2699
Swansea	0.4986	0.4979	0.2697	Man City	0.5014	0.5020	0.2697	Swansea	0.4934	0.4904	0.2697
Wolves	0.5009	0.5013	0.2699	Aston Villa	0.5075	0.5109	0.2700	Wolves	0.4981	0.4972	0.2699
West Brom	0.5056	0.5081	0.2698	Sunderland	0.5092	0.5133	0.2700	Everton	0.5004	0.5005	0.2699
Wigan	0.5112	0.5163	0.2697	Norwich	0.5108	0.5158	0.2699	Blackburn	0.5058	0.5084	0.2701
Arsenal	0.5147	0.5212	0.2693	Man United	0.5166	0.5241	0.2694	Chelsea	0.5066	0.5095	0.2696
Bolton	0.5156	0.5228	0.2697	Liverpool	0.5167	0.5242	0.2694	Aston Villa	0.5161	0.5235	0.2696
Fulham	0.5160	0.5232	0.2694	Wolves	0.5173	0.5252	0.2696	Bolton	0.5181	0.5263	0.2695
Chelsea	0.5195	0.5282	0.2690	Chelsea	0.5181	0.5262	0.2693	Man United	0.5209	0.5304	0.2691
Aston Villa	0.5232	0.5338	0.2692	Everton	0.5187	0.5272	0.2695	Liverpool	0.5221	0.5321	0.2690
Tottenham	0.5363	0.5530	0.2678	Tottenham	0.5216	0.5314	0.2690	West Brom	0.5231	0.5337	0.2692
Norwich	0.5428	0.5630	0.2674	Blackburn	0.5236	0.5345	0.2694	Tottenham	0.5279	0.5406	0.2686
Man United	0.5469	0.5689	0.2667	Bolton	0.5396	0.5581	0.2678	Arsenal	0.5283	0.5412	0.2685
Liverpool	0.5486	0.5714	0.2664	West Brom	0.5411	0.5604	0.2676	Norwich	0.5385	0.5565	0.2680
Man City	0.5809	0.6225	0.2605	Arsenal	0.5441	0.5646	0.2670	Man City	0.5514	0.5758	0.2660

Table D.2. Summary statistics for penalty kicks bias.

HOME				AWAY				OVERALL			
TEAM	Mean	Median	SD	TEAM	Mean	Median	SD	TEAM	Mean	Median	SD
Man City	0.4115	0.3809	0.2336	Wigan	0.4758	0.4576	0.2465	Man United	0.5743	0.5734	0.2270
Man United	0.4192	0.3855	0.2290	Bolton	0.4881	0.4736	0.2514	Blackburn	0.5802	0.5902	0.2400
Swansea	0.4952	0.4808	0.2420	Tottenham	0.5720	0.5773	0.2404	Bolton	0.6155	0.6325	0.2282
Blackburn	0.5156	0.5065	0.2435	West Brom	0.6185	0.6428	0.2369	Swansea	0.6248	0.6455	0.2281
Stoke	0.6185	0.6349	0.2260	Sunderland	0.6191	0.6446	0.2380	Wigan	0.6263	0.6462	0.2259
Norwich	0.6422	0.6695	0.2279	Wolves	0.6295	0.6520	0.2285	Man City	0.6275	0.6435	0.2198
Fulham	0.6425	0.6671	0.2242	Blackburn	0.6464	0.6780	0.2310	Stoke	0.6769	0.7070	0.2122
QPR	0.6534	0.6813	0.2223	Arsenal	0.6505	0.6750	0.2196	Fulham	0.6864	0.7207	0.2118
Chelsea	0.6651	0.6920	0.2148	Newcastle	0.6514	0.6812	0.2259	QPR	0.6948	0.7321	0.2101
Bolton	0.6746	0.7054	0.2143	Liverpool	0.6563	0.6821	0.2182	Liverpool	0.6954	0.7254	0.2016
Liverpool	0.6763	0.7043	0.2100	Aston Villa	0.6613	0.6918	0.2215	Tottenham	0.6965	0.7290	0.2035
Everton	0.7030	0.7383	0.2026	Chelsea	0.6745	0.7050	0.2140	West Brom	0.6981	0.7343	0.2067
Wigan	0.7037	0.7408	0.2037	Fulham	0.6806	0.7158	0.2162	Chelsea	0.7011	0.7330	0.2001
Aston Villa	0.7065	0.7441	0.2024	QPR	0.6821	0.7278	0.2270	Aston Villa	0.7107	0.7481	0.1998
Newcastle	0.7136	0.7528	0.1993	Everton	0.6826	0.7142	0.2107	Newcastle	0.7108	0.7497	0.2013
Sunderland	0.7215	0.7682	0.2011	Man United	0.6830	0.7143	0.2102	Norwich	0.7113	0.7506	0.2013
West Brom	0.7234	0.7635	0.1930	Swansea	0.6977	0.7405	0.2141	Sunderland	0.7114	0.7519	0.2021
Wolves	0.7247	0.7650	0.1923	Stoke	0.7000	0.7384	0.2079	Wolves	0.7148	0.7510	0.1957
Tottenham	0.7412	0.7889	0.1861	Norwich	0.7203	0.7655	0.2005	Everton	0.7197	0.7567	0.1931
Arsenal	0.7576	0.8039	0.1722	Man City	0.7533	0.8028	0.1782	Arsenal	0.7399	0.7798	0.1806

Acknowledgements

We would like to thank the anonymous reviewers whose comments have led to significant improvements in the paper, and Dr Magda Osman for the original contact in assessing this research hypothesis.

References

Agena Ltd. (2013). AgenaRisk Free Version. Retrieved online December 21, 2013, from Agena: Bayesian network and simulation software for risk analysis and decision support: http://www.agenarisk.com/products/free_download.shtml

Agnew, G., & Carron, A. (1994). Crowd effects and the home advantage. International Journal of Sport Psychology, 25(1), 53–62.

Anders, A., & Rotthoff, W. (2012). Are Home Field Advantage and Referee Bias Driven by the Fans? Evidence from Across the Ocean. Under review. Draft available at: http://ssrn.com/abstract=2026037

Boyko, R., Boyko, A., & Boyko, M. (2007). Referee bias contributes to home advantage in English premiership football. Journal of Sports Sciences, 25(11), 1185–1194. DOI:10.1080/02640410601038576

Buraimo, B., Forrest, D., & Simmons, R. (2010). The 12th man?: refereeing bias in English and German soccer. Journal of the Royal Statistical Society, 173, Part 2: 431-449. DOI: 10.1111/j.1467-985X.2009.00604.x

Clarke, S. R., & Norman, J. M. (1995). Home ground advantage of individual clubs in English soccer. The Statistician, 44, 509–521.

Constantinou, A. & Fenton, N. (2013). Determining the level of ability of football teams by dynamic ratings based on the relative discrepancies in scores between adversaries. Journal of Quantitative Analysis in Sports, 0(0): 1-14. DOI: 10.1515/jqas-2012-0036

Courneya, K., & Carron, A. (1992). The home advantage in sport competitions: A literature review. Journal of Sport and Exercise Psychology, 14(1), 13.

Dawson, P., Dobson, S., Goddard, J., & Wilson, J. (2007). Are football referees really biased and inconsistent?: Evidence on the incidence of disciplinary sanction in the English Premier League. Journal of the Royal Statistical Society: Series A (Statistics in Society), 170(1), 231–250. DOI: 10.1111/j.1467-985X.2006.00451.x

Dohmen, T. J. (2008). The Influence of Social Forces: Evidence from the Behavior of Football Referees. Economic Inquiry, 46(3), 411–424. DOI: 10.1111/j.1465-7295.2007.00112.x

Downward, P., & Jones, M. (2007). Effects of crowd size on referee decisions: Analysis of the FA Cup. Journal of Sports Sciences, 25(14), 1541–1545. DOI: 10.1080/02640410701275193

Fenton, N. E., Neil, M. & Caballero J. G. (2007). Using Ranked nodes to model qualitative judgements in Bayesian Networks. IEEE TKDE, 19(10), 1420-1432.

Fenton, N. E. & Neil, M. (2012). Risk Assessment and Decision Analysis with Bayesian Networks. CRC Press.

Garicano, L., Palacios-Huerta, I., & Prendergast, C. (2005). Favoritism under social pressure. Review of Economics and Statistics, 87(2), 208–216. DOI:10.1162/0034653053970267

Goumas, C. (2012). Home advantage and referee bias in European football. European Journal of Sport Science, iFirst article: 1-7. DOI:10.1080/17461391.2012.686062

Heuer, Andreas, and Oliver Rubner. (2009). Fitness, chance, and myths: an objective view on soccer results. *The European Physical Journal B* 67.3 (2009): 445-458. DOI: 10.1140/epjb/e2009-00024-8

Hirotsu, N., & Wright, M. (2003). An evaluation of characteristics of teams in association football by using a Markov process model. The Statistician, 52: 4, 591-602. DOI: 10.1046/j.0039-0526.2003.00437.x

Neave, N., & Wolfson, S. (2003). Testosterone, territoriality, and the'home advantage'. Physiology and Behavior, 78(2), 269–275. http://dx.doi.org/10.1016/S0031-9384(02)00969-1

Neil, M., Marquez, D. & Fenton, N. E. (2010). Improved Reliability Modeling using Bayesian Networks and Dynamic Discretization. Reliability Engineering & System Safety, 95(4), 412-425. http://dx.doi.org/10.1016/j.ress.2009.11.012

Nevill, A., Balmer, N., & Williams, A. (2002). The influence of crowd noise and experience upon refereeing decisions in football. Psychology of Sport and Exercise, 3(4), 261–272. http://dx.doi.org/10.1016/S1469-0292(01)00033-4

Nevill, A., Balmer, N., & Williams, M. (1999). Crowd influence on decisions in association football. Lancet, 353(9162), 1416.

Nevill, A., & Holder, R. (1999). Home advantage in sport: An overview of studies on the advantage of playing at home. Sports Medicine, 28(4), 221–236.

Nevill, A., Newell, S., & Gale, S. (1996). Factors associated with home advantage in English and Scottish soccer matches. Journal of Sports Sciences, 14(2), 181–186. DOI**:** 10.1080/02640419608727700

Page, K. & Page, L. (2010). Alone against the crowd: Individual differences in referees' ability to cope under pressure. Journal of Economic Psychology, 31: 192-199. http://dx.doi.org/10.1016/j.joep.2009.08.007

Pollard, R. (1986). Home advantage in soccer: A retrospective analysis. Journal of Sports Sciences, 4(3), 237–248. DOI: 10.1080/02640418608732122

Pollard, R. (2006). Worldwide regional variations in home advantage in association football. Journal of Sports Sciences, 24(3), 231–240. DOI: 10.1080/02640410500141836

Poulter, D. R. (2009). Home advantage and player nationality in international club football. Journal of Sports Sciences, 27(8): 797-805. DOI: 10.1080/02640410902893364

Pollard, R., & Pollard, G. (2005). Long-term trends in home advantage in professional team sports in North America and England (1876–2003). Journal of Sports Sciences, 23(4), 337–350. DOI: 10.1080/02640410400021559

Sutter, M., & Kocher, M. (2004). Favoritism of agents – The case of referees' home bias. Journal of Economic Psychology, 25(4), 461–469. http://dx.doi.org/10.1016/S0167-4870(03)00013-8

WhoScored?.com (2012). WhoScored?.com: Revolutionising Football Statistics. Retrieved online January 17, 2014, from England: Premier League 2011/12: http://www.whoscored.com/Regions/252/Tournaments/2/Seasons/2935