Research Paper E-ISSN No : 2455-295X | Volume : 2 | Issue : 5 | May 2016

THE RUGBY LEAGUE PREDICTION MODEL: USING AN ELO-BASED APPROACH TO PREDICT THE OUTCOME OF NATIONAL RUGBY LEAGUE (NRL) MATCHES

*Joel Carbone [1] | Tony Corke | Dr. Frank Moisiadis [1]

[1] University of Notre Dame, Sydney. (*Corresponding Author)

ABSTRACT

We introduce and discuss our model, which is used for rating teams in the National Rugby League (NRL) competition. It is an ELO-style model, modified to integrate several match variables into its calculations. Match data obtained from the 1999-2014 NRL seasons were used to build the model, and matches from the 2015 NRL season were used as a test sample. An automated computer system, employing an iterative approach, and written in R script, was used to optimise the parameters in the underlying ELO model. The model correctly predicted a total 63.0% of results, with a mean absolute error (MAE) of 13.7 points per game during the build process. The test phase saw a slightly better MAE – of 13.0 points per game – produced, and a lower accuracy of 55.7%. Secondary experiments regarding the model's ability to predict the top 8 at the end of the home-and-away season were also conducted.

KEYWORDS: NRL, rating, ELO, predictive, rugby league.

Introduction:

There has been an increased interest in predictive methods and their possible use in sports in recent years. This interest has driven teams in many major international sports leagues to employ strategies from predictive business methods into many of their practices in the search of a competitive advantage (Alamar, 2013).

The ELO rating system was developed by and named after Arpad Elo (Elo, 1978 as cited in Neumann, Duboscq, Dubuc, Ginting, Irwan, Agil, Widdig & Engelhardt, 2011) and is used for ratings in chess (Glickman, 1995), Soccer (Hvattum & Arntzen, 2010), American Football (Paine, 2015), Basketball (Silver & Fischer-Baum, 2015) and Baseball (Silver, 2006). The major difference to commonly used ranking methods is that ELO rating is based on the sequence in which interactions occur, and continuously updates ratings by looking at interactions sequentially (Neumann, et al., 2011). Despite its popularity, though, ELO ratings have rarely been used in rugby league ("National Rugby League - 2015 FINAL", 2015)

The National Rugby League (NRL) is the Australian national rugby league competition. It is comprised of 16 teams and consists of 26 rounds, with each club scheduled two bye rounds between rounds 10 and 20 of the regular season period. Following the regular season period, the top eight teams participate in a four week finals series to determine the premiership winning team each season (McLellan, 2010).

While major steps have been taken in both the study of, and introduction of objective analytic methods in Baseball (Yang & Swartz, 2004), Basketball (Kvam & Sokol, 2006), American Football (Ziemba, 2015) and Soccer (Hvattum & Arntzen, 2010; Constantinou, Fenton & Neil, 2012), as well as other predominantly Australian based sports, such as Australian Rules football (Ryall & Bedford, 2010) rugby league has seen no such outcome. There is a dearth of public information surrounding the NRL's use of such methods at a team organisation level. Analogous to this is the relative lack of study concerning technical and tactical performance in rugby league match play (Kempton, Kennedy & Coutts, 2015; Eaves & Broad, 2007; Sirotic, Knowles, Catterick, & Coutts, 2011). Methods of quantifying player and team tactical performance are scarce. However, there are several studies into the physical output of rugby league players, aided by the introduction of several micro technologies – namely global positioning systems and accelerometers (Gabbett, Jenkins, & Abernethy, 2012; Kempton, Sirotic, Rampinini, & Coutts, 2015; Waldron, Twist, Highton, Worsfold, & Daniels, 2011; as cited in Kempton, Kennedy & Coutts, 2015). These studies, useful as they are, cannot inform decisions regarding match outcomes to the extent of technical and tactical proficiencies (Rampinini, Impellizzeri, Castagna, Coutts, & Wisloff, 2009; Sullivan, Bilsborough, Cianciosi, Hocking, Cordy, & Coutts, 2014). The gap between studies concerning quantifying player and tactical performance and those concerning the physical output of rugby league players is significant. This paper introduces a model to minimise that gap.

The remainder of the paper is organised as follows. Section 1 provides insight into the methods used in both the build and test phases of the model's development. Section 2 presents the findings of the build and test phases, as well as some overall findings. Section 3 discusses the practical implications of the results and highlights limitations of the research. Section 4 provides a conclusion and outlines future work.

1. Method:

Data were obtained from all 3349 games from the 1999-2015 NRL seasons and stored using Microsoft Excel (Microsoft, 2010). These data were used for two purposes. Firstly, we developed an ELO-style team rating system that can be used to determine NRL team ratings on the basis of game outcomes and game venues. This was created using data from all 3148 NRL matches between 1999 and 2014. Secondly, we tested the model using an out of sample set (2015 NRL Season) to assess its predictive ability. Ethical clearance was granted prior to the commencement of this study.

The system incorporates, along with each team's current rating, 9 aspects of each game (Year, Round Number, Match Type, Home Team Name, Home Team Score, Away Team Name, Away Team Score, Venue, Region). This allows us to assess a team's performance in terms of the margin of victory they achieve relative to their own and their opponent's rating, taking into account the advantage that accrues to a home team from playing on their home ground, especially if their opponent needs to travel a considerable distance. For this purpose we created additional fields in which teams and venues were mapped to regions.

The process was adapted from the methods of Arpad Elo, a Hungarian born American physics professor (Ross, 2007). His ELO rating model is an earned rating system where ranking points are updated iteratively after every match. The main idea is that the update rule can be seen as a correction to the teams' rating points subject to actual results and what we expected from the ratings prior to the match (Lasek, Szlávik & Bhulai, 2013). The adapted ELO equation we used will be briefly described in this section.

All teams are set to an Initial Rating (I) at the beginning of the 1999 season. The Initial Rating, and therefore the mean rating moving forward was set to 1,000 (ie. I=1,000). Each subsequent team rating is derived by multiplying some multiplier (k) by the difference in actual margin and expected margin and adding this result to the teams previous weeks rating. The formula is:

$$R_{new} = R_{old} + k_n\,(\textit{Actual Margin-Expected Margin}) \tag{1}$$

Where:

- The Actual Margin is equal to the difference in points scored and points conceded.

$$\textit{Actual Margin=Points scored-Points conceded} \tag{2}$$

- k_n is equal to the multiplier.

- The Expected Margin is equal to the summation of the difference in team ratings (equal to the difference between two competing teams ratings), Inter-Regional Advantage (IRA) and Home Ground Advantage (HGA).

$$\text{Expected Margin} = (R_{old} - R_{opposition}) + \textit{IRA} + \textit{HGA} \tag{3}$$

Ratings changes occur after a match has been completed and affect the assessment of a team's victory chances in future games. The difference in team ratings between two teams describes the expected margin in a game between them if that game was played on a neutral ground. Each game has a zero-sum effect on the 2 teams involved (i.e. the rating points gained by one team will be exactly equal to the rating points lost by their opponents). The 2014, round 23 match between the Penrith Panthers (Panthers) and the Melbourne Storm (Storm) will be used to demonstrate this. Prior to the match the Panthers and Storm had ratings of 1,003.2 and 1,004.8, respectively. The outcome of the match was a 24-10 win for the Storm, which effected an improvement in their rating, to 1,006.1. This simultaneously initiated a regression in the Panthers rating to 1,001.9, which conveys a decline of 2.9 ratings points, the exact value of the Storm's rating improvement.

1.1 Build:

We processed data sets using an automated computer script that facilitated the choice of optimal parameters in the underlying ELO model. An R script (R Core Team, 2015) was created for this purpose and the resulting model was used for fitting and prediction. Parameters of the rating system have been optimised to minimise the mean absolute error (*MAE*) of the resulting forecasts over the testing period. MAE was selected as the preferred method of model evaluation, as opposed to other measures, such as the root mean square error (*RMSE*). It is determined that dimensioned evaluations and inter-comparisons of average model-performance error, should be based on MAE, as opposed to RMSE. The lack of ambiguity and ability to provide a more natural indication of average error informs this decision (Willmott & Matsuura, 2005).

Several intra-season multipliers (k_n) are used to adjust ratings and account for changes in conditions during stages in the season. Each multiplier serves to translate the difference in the actual result relative to expectation into a ratings change. A larger multiplier means that a given difference has a larger effect in the resulting ratings change. We found that using 4 intra-season multipliers provided the optimal result. The first multiplier (k_1=0.057) facilitates the model recalibrating to the ‘true’ abilities of the teams early in the season between Rounds 1-11; the middle portion of the season – (Rounds 12-17) where State of Origin is played and teams frequently have key players unavailable – has a relatively small multiplier (k_2=0.044); the final part of the home and away season carries the most weight (k_3= 0.099). We found that the actual optimum finals multiplier was slightly negative. This has the unfortunate effect of reducing teams rating if it performs above expectation, which is illogical. We have set the finals multiplier to zero (k_4=0), although this has a relatively small effect on the final results.

A cap (*m*) on maximum margin of victory was instituted to ensure that blowout victories do not overly inflate team rating changes. We have determined that any margin of victory greater than approximately 7 converted tries (*m*=43) will have excessive effects on the ratings of the teams involved. Therefore, any team that wins or loses by a margin greater than 42 points will have their victory, or loss, capped for the purposes of rating updates.

Home Ground Advantage (HGA) is applied according to the calculated value of a team’s advantage at a particular home ground. A fixed HGA of 0.7 points is applied to games played on a neutral ground between teams from the same region. We use 27 different team-venue combinations (Figure 1). A team is assigned a home ground advantage if they have played more than 20 games at a particular venue, with these values also determined by an optimisation process. The average HGA is 2.98 points.

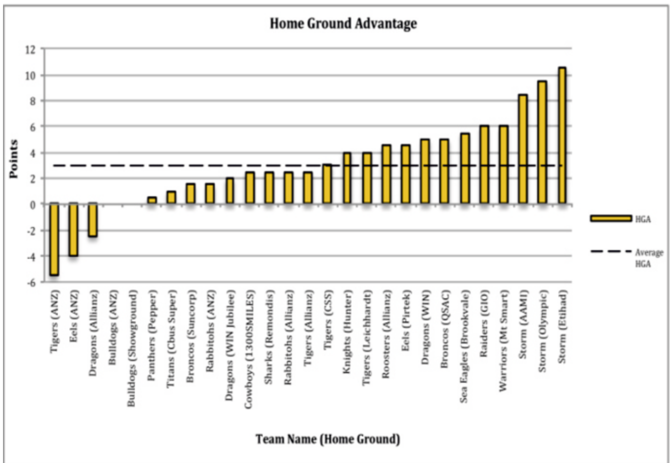

Figure 1. Calculated value of HGA for all teams at venues with 20 or more matches played. **

Inter-Regional Advantage (IRA) is applied according to the calculated value of a team’s advantage in a particular region, when its opponent is not from that same region. An IRA of 0.3 is applied to teams playing a home game against another team from a different region; 8 regions*** in total have been used.

A carryover parameter (p) allows us to reflect the previous season rating at the start of a new season, recognising that there are changes that occur during the offseason (player turnover, attrition, aging, coaching changes), but that teams nevertheless carry some of the previous season’s ability into the next. We estimated an optimal value of p=0.24. This means that a team will carry 24% of its final rating surplus or deficit (above or below 1,000, respectively) in one season into the next. Effectively, the team regresses or improves by 76% towards the mean rating of 1,000. Teams whose ratings are either very large or very small at the conclusion of a season see their rating change most. e.g. A team who finishes the season with a rating of 990 will begin the following season with a rating of 997.6 (improving 7.6 rating points) whereas a team with an end of season rating of 1,002 will begin the following season with a rating of 1,000.5 (regressing 1.5 ratings points).

The model’s accuracy in estimating match results, and the MAE of its estimated margins across the entire build period was calculated. Also calculated was the model’s alignment with the top 8 teams at the end of the home-and-away season. We also describe team rating characteristics and map them to final season outcomes such as grand final appearances and premierships won.

1.2 Test:

Data from all 201 competition matches from the 2015 season were retained to provide an out of sample data set for testing purposes. The model’s performance was assessed using the same metrics as just described.

2. Results

After building the model using data from the 1999-2014 NRL seasons, we tested it against an out-of data set from the 2015 NRL season. The model’s performance was tested in 2 key areas in both the build and test stages. These areas are:

1. Accuracy in predicting head-to-head results
2. MAE per game

Some additional, macro measures were also used to assess the model’s utility:

3a. How many of the model’s top 8 rated teams finish inside the actual top 8?

3b. Is the model better than the ladder at predicting the top 8 from the halfway point of the season?

4. What are the ratings characteristics of the preliminary finalists (final four teams remaining), Grand Final participants and premiers?

2.1 Results of the Build:

1. We correctly predicted match outcomes in 63.0% of all cases. Figure 2 shows the yearly accuracy for all seasons 1999-2014 compared with this overall average.

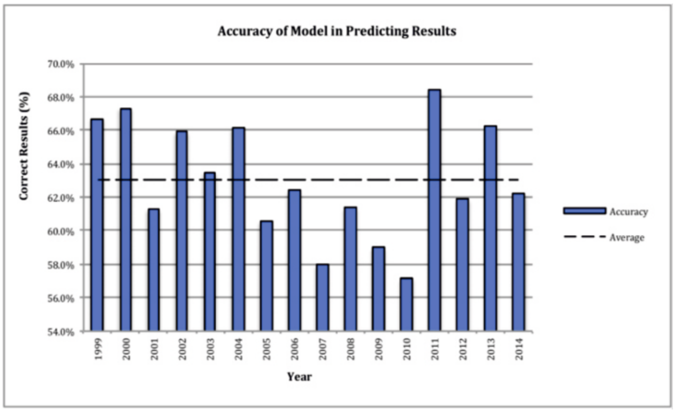

Figure 2. Yearly accuracy in predicting match results compared to the average across the build.

2. We calculated a MAE of 13.7 points per game. On a season-by-season basis, the performance spanned a low of 11.6 points in 2011 and a high of 14.9 points in 2004 (Figure 3). Supplementing this, a summary of mean error, median error and standard error (Table 1) are provided across all seasons of the build.

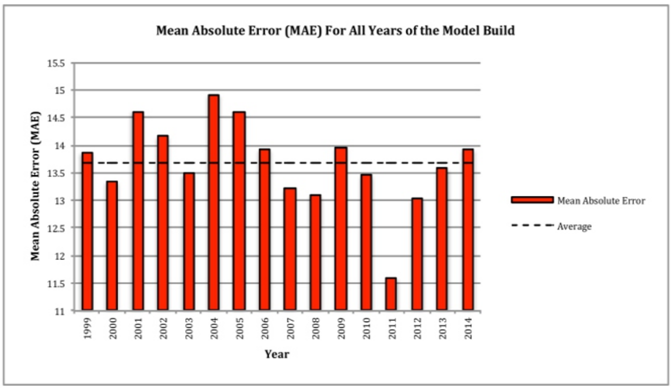

Figure 3. MAE compared to the average across all seasons of the build.

Table 1. Alternate error measurements compared to MAE for the period of the build.

Year	Number of Games Played	Mean Error	Median Error	MAE	SD Error
1999	213	0.31	-0.18	13.88	17.82
2000	191	3.08	1.20	13.35	17.36
2001	191	-0.04	-0.50	14.61	18.77
2002	189	0.86	0.96	14.16	18.08
2003	189	-2.29	-2.66	13.49	17.09
2004	189	1.37	0.44	14.92	19.00
2005	189	1.45	1.32	14.58	18.37
2006	189	-1.99	-2.76	13.94	17.77
2007	201	2.30	-0.10	13.21	16.97
2008	201	1.96	0.69	13.10	16.60
2009	201	0.43	0.18	13.97	17.33
2010	201	0.93	0.23	13.47	16.79
2011	201	-0.07	0.69	11.60	14.74
2012	201	-1.21	-0.67	13.04	16.41
2013	201	0.59	-0.05	13.57	17.60
2014	201	0.72	0.20	13.93	17.39

3a. The model's end-of-season team ordering based on final ratings exhibited high levels of agreement with the final home-and-away NRL ladders. Of the 128 finals participants over the 16 seasons the build oversaw, 108 of them (84.4%) were amongst the 8 highest-rated teams at the end of the respective seasons. However, three teams * – the 2002 Canterbury Bulldogs (Bulldogs) (Walters & Masters, 2002), 2006 New Zealand Warriors (Williams, 2006) and 2010 Storm (Barrett, 2010) – were stripped of competition points for salary cap infractions, which resulted in them being excluded from finals. In each case, had they not been penalised, all 3 teams would have finished inside the top 8. Two were also amongst the 8 highest-rated teams according to the model and Table 2 shows the final results after including these teams. The overlap between the model's top 8 teams and competition finalists was 110/128 (85.9%). That's equivalent to an overlap of about 6.9 out of 8 teams per season.

Table 2. Overlap of teams who finished in the top 8 in both the model's rating position and the ladder at the end of the home-and-away season.

Year	Total Teams Overlapped	% Correct
1999	6	75.0%
2000	7	87.5%
2001	8	100.0%
2002	7	87.5%
2003	7	87.5%
2004	7	87.5%
2005	6	75.0%
2006	7	87.5%
2007	6	75.0%
2008	7	87.5%
2009	6	75.0%
2010	8	100.0%
2011	7	87.5%
2012	7	87.5%
2013	7	87.5%
2014	7	87.5%

3b. Similarly, the model showed a strong ability to predict the finals participants from the halfway point (after Round 13) of the season, compared to the ladder position of teams at that point.

- Of the 128 teams who sat in the top 8 on the ladder at the halfway point of the season, 93 (or 72.7%) finished the home-and-away season in the top 8.

- Of the 128 teams who sat in the top 8 in the model's ratings at the halfway point of the season, 99 (or 77.3%) went on to make the top 8.

In other words, the model ratings predicted an average of 6.19 (77.4%) of the finals participants, to the ladder's 5.81 (72.6%) per season. Table 3 presents an extended overview of the predictive abilities of the rating system as opposed to the ladder.

Table 3. Comparison of top 8 teams predicted from the halfway point (after round 13) of the season by the model's ratings and the ladder.

Year	Ratings Accuracy	Ladder Accuracy	Which Predicted Results Better? (By How Many?)
1999	7	5	Ratings (2)
2000	7	6	Ratings (1)
2001	6	6	-
2002	6	5	Ratings (1)
2003	7	8	Ladder (1)
2004	6	5	Ratings (1)
2005	7	6	Ratings (1)
2006	6	6	-
2007	5	4	Ratings (1)
2008	6	5	Ratings (1)
2009	6	6	-
2010	4	5	Ladder (1)
2011	7	7	-
2012	6	7	Ladder (1)
2013	6	6	-
2014	7	6	Ratings (1)
Total	**99**	**93**	**Ratings (6)**

4. We found that the average rating of a team that participates in the preliminary finals is 1,006.1, or about 6.1 points better than an 'average' team. Figure 4 shows the best team to advance to the preliminary finals were the 2004 Bulldogs, with a rating of 1,017.0. In contrast, the lowest rated individual team to advance to the preliminary finals were the 2014 Bulldogs (997.3), who had the added distinction of being the only Grand Final participant to have a rating lower than the mean of 1,000. Of the teams who have participated in the Grand Final, the average is 1,006.0 for the losing team and 1,008.1 for the victorious team (and premier). The 2001 Parramatta Eels (Eels) have the highest rating of any losing Grand Final team (1,013.3), while the aforementioned 2014 Bulldogs have the lowest rating. Of the Grand Final winners, and thus, premiers, the aforementioned 2004 Bulldogs had the highest rating (1,017.0) while the 1999 Storm had the lowest (1,001.0). Grand Finals were won by 11/16 teams (68.8%) with higher ratings than their opponents. The biggest Grand Final upset – a disparity between teams of 6.9 rating points - was recorded in 2001, when the Eels (1,013.3) were beaten by the Newcastle Knights (1,006.4).

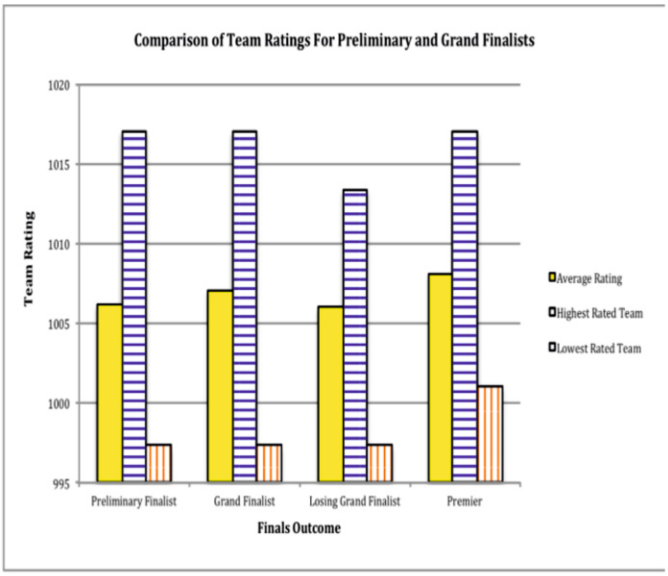

Figure 4. Average rating of preliminary finalists and Grand Finalists (Premiers and runners-up). The best and worst rated teams for each are displayed also.

2.2 Results of the Test

1. We correctly predicted 55.7% of match outcomes in 2015, 1.5% lower than the previously worst mark set in 2010 (57.2%). The overall average (1999-2015), thus, is negatively affected, decreasing the average prediction rate to 62.6%.

2. Despite the decline in match outcomes predicted, MAE still improved relative to the build. A MAE of 13.1 points per game was calculated, which exhibited a 0.6 points improvement compared to the average during the build (13.7).

3a. The final model ratings showed a significant overlap with the final home and away ladder. The model accounted for 7 of the 8 top 8 teams (Table 4), with the exception being the St George-Illawarra Dragons (Dragons). The Dragons had a rating of 998.9, the 9th-highest rating, but finished 8th in the final home-and-away ladder. Only 7 teams in 2015 finished with a rating above 1,000, and of these 6 finished in the top 8. The Manly Sea Eagles were the exception – they ended the season with a rating of 1,001.1 (the 7th highest rated team), but missed the top 8, finishing 9th.

Table 4. Overlap of 2015 team ratings with ladder position at the end of the home-and-away season (after 26 rounds).

Ratings Position After 26 Rounds	Rating	Ladder Position After 26 Rounds	Ladder Position
Sydney Roosters	1,012.9	Sydney Roosters	1
Brisbane Broncos	1,008.9	Brisbane Broncos	2
North Queensland Cowboys	1,008.0	North Queensland Cowboys	3
Melbourne Storm	1,003.8	Melbourne Storm	4
Canterbury Bulldogs	1,003.4	Canterbury Bulldogs	5
Cronulla Sharks	1,001.6	Cronulla Sharks	6
Manly Sea Eagles	1,001.1	South Sydney Rabbitohs	7
South Sydney Rabbitohs	998.9	St George-Illawarra Dragons	8

3b. The ratings system again displayed an aptitude for predicting the top 8 participants from the halfway point of the season in the test phase. Table 5 shows the outcome of the test period, where 7 of the 8 (87.5%) finals participants were predicted by the ratings, taking the total across the build and test to 106/136 (77.9%) teams predicted. This is compared to a total of 100/136 (73.5%) predicted using the ladder positions at the halfway point of the season.

Table 5. Comparison of teams predicted to make the top 8 by ratings position and ladder position at the completion of round 13.

Rating Position After 13 Rounds	Rating	Ladder Position After 13 Rounds	Final Ladder	Predicted by Ratings?
Sydney Roosters	1,005.2	Brisbane Broncos	Sydney Roosters	Yes
Brisbane Broncos	1,004.7	North Queensland Cowboys	Brisbane Broncos	Yes
South Sydney Rabbitohs	1,003.0	Melbourne Storm	North Queensland Cowboys	Yes
North Queensland Cowboys	1,002.9	St George-Illawarra Dragons	Melbourne Storm	Yes
St George-Illawarra Dragons	1,002.5	South Sydney Rabbitohs	Canterbury Bulldogs	Yes
Melbourne Storm	1,002.3	Sydney Roosters	Cronulla Sharks	No
Canterbury Bulldogs	999.4	Canterbury Bulldogs	South Sydney Rabbitohs	Yes
Canberra Raiders	999.4	New Zealand Warriors	St George-Illawarra Dragons	Yes
			Total	**7/8 (87.5%)**

4. The average rating of the teams who participated in the preliminary finals was 1,008.4, with both the highest rated – the Sydney Roosters (1,012.9) – and the lowest – the Storm (1,003.8) – failing to progress to the Grand Final. The average rating of the Grand Final teams showed a small marginal increase – there was an average of 1,008.4. This was due to a relatively small difference between the participants – the Brisbane Broncos (1,008.9) and the Cowboys (1,008.0). Figure 5 displays the average point differential between these teams and those from the build phase, all of which are higher in the test stage.

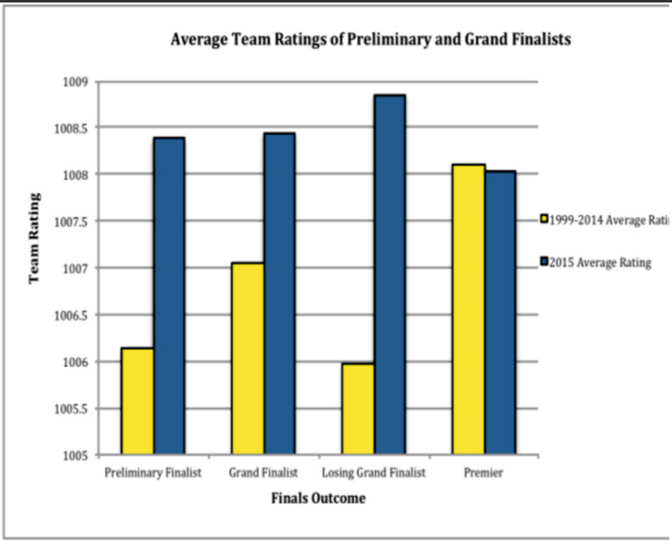

Figure 5. Comparison of preliminary and Grand Finalists team ratings in the build and test phases.

3. Discussion

This study determined the integrity of an automated ELO-style model in predicting the outcome of rugby league matches by creating a model using game data from the 1999-2014 NRL seasons. In addition, we calculated the expected ratings of teams who participate in finals and the ability of the model to predict the top 8 teams, as well as the premiership winners. The model was tested on an out-of-study sample and revealed a positive relationship between the actual and expected results throughout an NRL season. A secondary aim was to test the model's ability to predict the top 8, and thus the teams who participate in the finals each year. Conversely, the model should then be able to assess the level of teams who miss out on a finals position each year.

The results of this study provide a foundation for current playing strategies and provide a framework for match analyses in professional rugby league. Being able to determine the true position of a team has implications in team evaluation, individual game strategy and strength of schedule calculation (Hunter, 2014; Medeiros, 2014). This is demonstrated in the model's ability to correctly account for finals teams, which was especially successful when the calculations were adjusted to factor in teams who were removed from finals contention due to salary cap breaches (Table 2). Further, the model showed that teams who were rated in the model's top 8 after round 13 were more likely to make the finals than teams who actually sat inside the top 8 according to the NRL ladder. We found that the model correctly predicted 106/136 (77.9%) finals participants compared with 100 /136 (73.5%) predicted by the ladder. Therefore, we suggest a team is more likely to predict their future finals appearance status by employing these techniques, rather than focusing on their position on the ladder. Finally, the model was used to assess the ability of the preliminary finalists, Grand Finalists and premiers (Figure 5). We found that ratings characteristics were consistent across the build and test phases. Preliminary finalists had an average rating of 1,006.1 in thebuild, which increased in the small sample of the test (1 season) to 1,008.4. On average, the teams participating in the 2015 finals were 2.3 points better than those in the previous 16 years. The average ratings of the Grand Final participants displayed similar revelations, with the average rating of participants in the build phase 1,007.0, compared to 1,008.4 in the test. Therefore, the 2015 Grand Final Participants were, on average, 1.4 points better than those from 1999-2014. We found that the premiers in the build had an average rating of 1,008.1, which was almost identical to the 2015 premiers, the Cowboys, who the model rated 1,008.0. Finally, the model revealed a robust aptitude in picking Grand Final winners. Of the 17 total Grand Final winners (across the build and test) the model predicted 12 winners (70.6%) compared to 10 winners (58.8%) predicted using ladder position at the end of the home-and-away season. Employing strategies from the model's results (Figure 2, Figure 3 & Table 1) would allow teams an effective quantitative means of determining their own abilities relative to their competition, and provide perspective on any future decisions.

This model has several improvements due, both in terms of internal adjustments and the addition of new metrics to test. The internal adjustments are as follows:

- A dynamic HGA would allow the model to change the value of the advantage teams possess at home during the course of a season.
- IRA adjustments, where distance travelled and mode of transport are taken into consideration, should also improve the model's MAE.

To compliment these internal adjustments, additional sources of external information are required to improve the model's performance. The use of just 9 game metrics is a major limitation of this study. Testing the effectiveness of other game metrics in deciding the outcome of matches will allow further assessment of which variables are most predictive. Other external adjustments are as follows: testing individual games metrics to determine which are positive and negative predictive factors; testing the effects of player availability on match outcomes; testing the value of players according to their output. This will ultimately have further implications towards team building, salary cap management, individual game strategy, player development and player evaluation.

4. Conclusions and future work

The results of this study demonstrate the model's predictive aptitude and consistency over the build and test periods - we correctly predicted a total 62.6% of results, with a MAE of 13.6 points per game. While the information input was limited, the model was able to produce reasonable results and sufficiently precise predictions about each game. Additionally, we provide a framework for teams to analyse their performance relative to their competition in a quantifiable capacity. We intend to further our research by testing both internal and external adjustments on the model, and calculating the output. This will allow us to better assess the model's predictive capabilities and present specific game strategies for teams to employ.

Notes

* A further 2 teams - The 2000 Cowboys and the 2009 Bulldogs (Jancetic, 2009) had competition points deductions, although these had no effect on either team's ladder position.

** **Table 6. Abbreviations used for 'Figure 1. Calculated value of HGA for all teams at venues with 20 or more matches played from 1999-2014.'**

Abbreviation	Home Ground
ANZ	ANZ Stadium
Allianz	Dragons (Allianz Stadium)
Pepper	Pepper Stadium
Cbus Super	Cbus Super Stadium
Suncorp	Suncorp Stadium
WIN Jubilee	WIN Jubilee Oval
1300SMILES	1300SMILES Stadium
Remondis	Remondis Stadium
CSS	Campbelltown Sports Stadium
Hunter	Hunter Stadium
Leichhardt	Leichhardt Oval
Pirtek	Pirtek Stadium
WIN	WIN Stadium
QSAC	Queensland Sport and Athletics Centre
Brookvale	Brookvale Oval
GIO	GIO Stadium
Mt Smart	Mt Smart Stadium
AAMI	AAMI Park
Olympic	Olympic Park
Etihad	Etihad Stadium

*****Table 7. Teams and venues used for region mapping.**

Region	Teams in Region	Venues in Region
Sydney	Western Suburbs Magpies, North Sydney Bears, Sydney Roosters, South Sydney Rabbitohs, Canterbury Bulldogs, Penrith Panthers, Cronulla Sharks, Balmain Tigers, Parramatta Eels, St George-Illawarra Dragons, Manly Sea Eagles, Wests Tigers, Northern Eagles	Pepper Stadium, Pirtek Stadium, Leichhardt Oval, Brookvale Oval, Sydney Cricket Ground, North Sydney Oval, Campbelltown Sports Stadium, Sydney Showground, Allianz Stadium, Remondis Stadium, ANZ Stadium, WIN Jubilee Oval, WIN Stadium, Glen Willow Sporting Complex, Carrington Park, Belmore Sports Ground
Newcastle	Newcastle Knights	Hunter Stadium, Central Coast Stadium
Canberra	Canberra Raiders	GIO Stadium
Melbourne	Melbourne Storm	Melbourne Cricket Ground, Etihad Stadium, AAMI Park, Olympic Park
Brisbane	Brisbane Broncos	Queensland Sport and Athletics Centre, Suncorp Stadium
Gold Coast	Gold Coast Titans	Cazaly's Stadium, Cbus Super Stadium
North Queensland	North Queensland Cowboys	1300SMILES Stadium, Virgin Australia Stadium, Barlow Park
New Zealand	New Zealand Warriors	Mt Smart Stadium, Westpac Stadium, AMI Stadium, Waikato Stadium, Eden Park, Owen Delany Park, McLean Park
Other	-	Lathlain Park, Manuka Oval, nib Stadium, Coopers Stadium, Adelaide Oval, Marrara Stadium, Domain Stadium, Lavington Sports Ground

REFERENCES

1. Alamar, B. (2013). Sports Analytics: A Guide for Coaches, Managers and Other Decision Makers. New York, NY: Columbia University Press.
2. Barrett, C. (2010, April 22). Melbourne Storm stripped of premierships for salary cap breaches. The Sydney Morning Herald. Retrieved from http://www.smh.com.au/rugby-league/league-news/melbourne-storm-stripped-of-premierships-for-salary-cap-breaches-20100422-td91.html
3. Constantinou, A. C., Fenton, N. E., & Neil, M. (2012). pi-football: A Bayesian network model for forecasting Association Football match outcomes.Knowledge-Based Systems, 36, 322-339.
4. Eaves, S., & Broad, G. (2007). A comparative analysis of professional rugby league football playing patterns between Australia and the United Kingdom. International Journal of Performance Analysis of Sport, 7(3), 54–63.
5. Gabbett, T., Jenkins, D., & Abernethy, B. (2012). Physical demands of professional rugby league training and competition using microtechnology. Journal of Science and Medicine in Sport, 15(1), 80–86.
6. Glickman, M. E. (1995). The glicko system. Boston University.
7. Hunter, L. (2014, July 21). How Sports Data Analytics Is Upsetting The Game All Over Again. Retrieved from http://www.fastcolabs.com/3033324/how-sports-data-analytics-is-upsetting-the-game-all-over-again
8. Hvattum, L. M., & Arntzen, H. (2010). Using ELO ratings for match result prediction in association football. International Journal of forecasting, 26(3), 460-470.
9. Jancetic, S. (2009, April 4). Bulldogs stripped of two NRL points. Retrieved from http://www.theroar.com.au/2009/04/04/bulldogs-stripped-of-two-nrl-points/
10. Kempton, T., Kennedy, N., & Coutts, A. J. (2015). The expected value of possession in professional rugby league match-play. Journal of sports sciences, 1-6.
11. Kempton, T., Sirotic, A., Rampinini, E., & Coutts, A. J. (2013). Match-related fatigue reduces physical and technical performance during elite rugby league match-play: A case study. Journal of Sports Sciences, 31(16), 1770–1780.
12. Kvam, P., & Sokol, J. S. (2006). A logistic regression/Markov chain model for NCAA basketball. Naval Research Logistics (NrL), 53(8), 788-803.
13. Lasek, J., Szlávik, Z., & Bhulai, S. (2013). The predictive power of ranking systems in association football. International Journal of Applied Pattern Recognition, 1(1), 27–46.
14. McLellan, C. P. (2010). NEUROMUSCULAR, BIOCHEMICAL, ENDOCRINE AND PHYSIOLOGICAL RESPONSES OF ELITE RUGBY LEAGUE PLAYERS TO COMPETITIVE MATCH-PLAY (Doctoral dissertation, Bond University).
15. Medeiros, J. (2014, January 23). The winning formula: data analytics has become the latest tool keeping football teams one step ahead. Retrieved from http://www.wired.co.uk/magazine/archive/2014/01/features/the-winning-formula
16. Microsoft. (2010). Microsoft Excel [computer software]. Redmond, Washington: Microsoft.
17. Neumann, C., Duboscq, J., Dubuc, C., Ginting, A., Irwan, A. M., Agil, M., Widdig, A., & Engelhardt, A. (2011). Assessing dominance hierarchies: validation and advantages of progressive evaluation with Elo-rating. Animal Behaviour, 82(4), 911-921.
18. National Rugby League - 2015 FINAL. (2015). Retrieved from http://www.rugbyleagueratings.com/2015nrl.php
19. Paine, N. (2015, September 10). NFL Elo Ratings Are Back!. Retrieved from http://fivethirtyeight.com/datalab/nfl-elo-ratings-are-back/
20. R Core Team (2015). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. http://www.R-project.org/.
21. Rampinini, E., Impellizzeri, F. M., Castagna, C., Coutts, A. J., & Wisloff, U. (2009). Technical performance during soccer matches of the Italian Serie A league: Effect of fatigue and competitive level. Journal of Science and Medicine in Sport, 12(1), 227-233.
22. Ross, D. (2007, December 16). Arpad Elo and the Elo Rating System. Retrieved from http://en.chessbase.com/post/arpad-elo-and-the-elo-rating-system
23. Ryall, R., & Bedford, A. (2010). An optimized ratings-based model for forecasting Australian Rules football. International Journal of Forecasting, 26(3), 511-517.
24. Sullivan, C., Bilsborough, J., Cianciosi, M., Hocking, J., Cordy, J., & Coutts, A. J. (2014). Match score affects activity profile and skill performance in professional Australian football players. Journal of Science and Medicine in Sport, 17(3), 326–331.
25. Silver, N., & Fischer-Baum, R. (2015, May 21). How We Calculate NBA Elo Ratings. Retrieved from http://fivethirtyeight.com/features/how-we-calculate-nba-elo-ratings/
26. Silver, N. (2006, June 28). Lies, Damned Lies. Retrieved from http://www.baseballprospectus.com/article.php?articleid=5247
27. Sirotic, A., Knowles, H., Catterick, C., & Coutts, A. J. (2011). Positional match demands of professional Rugby League Competition. Journal of Strength and Conditioning Research, 25(11), 3076–3087.
28. Waldron, M., Twist, C., Highton, J., Worsfold, P., & Daniels, M. (2011). Movement and physiological match demands of elite rugby league using portable global positioning systems. Journal of Sports Sciences, 29(11), 1223–1230.
29. Walters, B., & Masters, R. (2002, August 24). Bulldogs stripped of points. The Age. Retrieved from http://www.theage.com.au/articles/2002/08/23/1030052974663.html
30. Williams, S. (2006, February 27). Warriors docked points and fined. Retrieved from http://leagueunlimited.com/news/warriors-docked-points-and-fined#MIWBu6g3ALkmzeIq.97
31. Willmott, C. J., & Matsuura, K. (2005). Advantages of the mean absolute error (MAE) over the root mean square error (RMSE) in assessing average model performance. Climate research, 30(1), 79.
32. Yang, T. Y., & Swartz, T. (2004). A two-stage Bayesian model for predicting winners in major league baseball. Journal of Data Science, 2(1), 61-73.
33. Ziemba, B. (2015). The 2014–2015 NFL Season, Playoffs, and the Super Bowl.Wilmott, 2015(77), 24-43.