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PREDICTION OF FINAL FOOTBALL LEAGUE STANDINGS BY DYNAMIC FRONTIER ESTIMATION

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PREDICTION OF FINAL FOOTBALL LEAGUE STANDINGS
BY DYNAMIC FRONTIER ESTIMATION

MELİKE YILMAZ
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APPROVED BY:

Assist. Prof. Dr. S. Tankut Atan (Thesis Supervisor)	Işık University	____________
Assoc. Prof. Dr. S. Çağlar Aksezer (Thesis Co-Supervisor)	Işık University	____________
Assist. Prof. Dr. Demet Ö. Ünlüakın	Işık University	____________
Assist. Prof. Dr. Burak Çavdaroğlu	Kadir Has University	____________

APPROVAL DATE: ..../..../....

PREDICTION OF FINAL FOOTBALL LEAGUE STANDINGS BY DYNAMIC FRONTIER ESTIMATION

Abstract

Data Envelopment Analysis (DEA) is a commonly used method for efficiency assessment of teams in many sports including football. In this work, we investigate how estimations of final league standings with DEA efficiency measures evolve as the season progresses using Turkish first division football league data for five seasons. After the conclusion of each week, a DEA analysis is run using available data until then, and computed efficiencies are used to estimate the final table standings. While the estimates fluctuate early in the season, they tend to stabilize after several weeks. Tracking the weekly progress of the results may give the teams a chance to finish in a better position by focusing on their inefficiencies. Furthermore, the choice of the DEA linear programming model makes a difference in the quality of the results. Estimations are improved by using a model that incorporates expert knowledge about football.

Keywords: Data Envelopment Analysis (DEA), Assurance Region Model, Football Efficiency, Turkish Football Clubs

DİNAMİK ÖNCÜ METOTLAR KULLANARAK FUTBOL LİGİNİN PUAN SIRALAMASININ TAHMİNİ

Özet

Veri Zarflama Analizi (VZA) metodu, futbol dahil olmak üzere birçok takım sporunun verimlilik değerlendirmesi için yaygın olarak kullanılmaktadır. Bu çalışmada, Türkiye'de birinci ligde oynayan futbol takımlarının performansları son beş yıllık gerçek veri ile analiz edilip değerlendirilmektedir. Çalışmanın amacı, performans özelliklerini kullanarak lig sonunda oluşması muhtemel sıralamayı sezon içerisinde olabildiğince erken tahmin etmektir. Sezonun başındaki tahmin doğrululuk oranı düşük olurken, sezon haftaları geçtikçe kayda değer seviyelere çıkmaktadır. Yapılan haftalık analizler sonrasında, her karar noktası yani takımın etkinlik değeri hakkında bilgiler elde edilmektedir. Bu bilgiler kullanılarak takımların zayıf yönlerine yönelik hamleler yapması ve sezonu daha iyi bir sırada bitirmesi mümkün olacaktır.

Anahtar kelimeler: Veri Zarflama Analizi (VZA), Güven Bölgesi (AR) Yöntemi, Futbol Verimliliği, Türkiye Futbol Kulüpleri

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To my family and friends…

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List of Abbreviations

AHP	**A**nalytical **H**ierarcy **P**rocess
AR	**A**ssurance **R**egion
AR-I-C	**I**nput **O**riented **A**ssurance **R**egion Model
CCR	**C**harnes **C**ooper **R**hodes
CCR-I	**I**nput **O**riented **C**harnes **C**ooper **R**hodes Model
CI	**C**onsistency **I**ndex
CR	**C**onsistency **R**atio
CRS	**C**onstant **R**eturns to **S**cale
DEA	**D**ata **E**nvelopment **A**nalysis
DMU	**D**ecision **M**aking **U**nit
LP	**L**inear **P**rogramming
NBA	**N**ational **B**asketball **A**ssociation
NFL	**N**ational **F**ootball **L**eague
RI	**R**andom Consistency **I**ndex
SFA	**S**tochastic **F**rontier **A**nalysis
TFF	**T**urkish **F**ootball **F**ederation
UEFA	**U**nion of **E**uropean **F**ootball **A**ssociations
VRS	**V**ariable **R**eturns to **S**cale

Chapter 1

Introduction

Besides being the most popular sport in terms of followers and fans, football is a multibillion dollar industry that dominates the sports economics. Without doubt, European football clubs and managing bodies are the prominent stakeholders of this industry. Szymanski [1] provides a diverse collection of challenges faced in this arena since early 90's, especially focused on Euro area. European football holds several financial earning records for any professional sport on the face of the planet. According to Harris [2] , United Kingdom (UK) Premier League is the most broadcasted league in the world with earnings from TV rights of more than $2.5 billions per year being second best only after NFL. It also holds several top spots in the list of international clubs with most expensive sponsorship deals signed. Teams from UK and Spain are earning vast sums of money from selling their jersey and arena naming rights. More importantly, record amount of prize money is distributed to competitor clubs through organizations such as European Football Associations (UEFA) Champions League with total prize money well over billion dollars.

In order to get a larger slice of the cake, teams try to achieve higher international recognition and dominance over each other. Consecutive appearances in international organizations is the major key to this success. Teams qualify for such organizations when they secure a certain top spot in their final national league standing. Turkish national league, which is named "Spor Toto Süper Lig", contains 18 top division clubs. A total 34 home and away games are played by each team with a Federation Cup tournament. Champion of the league is directly qualified for UEFA Champions League; the runner up should plays certain rounds of qualification matches. A certain number of consecutive seeders are qualified for the UEFA Europa League, which is the other international organization with slightly less prestige and financial earnings.

Turkey's football industry gained critical acclaim during recent years as it improves drastically in terms of financial winning and losses. An in-depth historical background of Turkish football is provided by Senyuva and Tunc [3]. Clubs have earned large amounts of money from the sale of broadcasting rights and gained higher fan attendance as the construction of new generation stadiums completed. On the other hand, they also faced massive budgetary deficits because of operating losses mainly occurring from astronomic transfer fees. Some of the clubs were even banned from international organizations because of the regulatory financial play rules. Some studies suggest that these economical factors have socio-psychological impacts on the society as well. Berument and Yücel [4] provide the statistical basis of relation between Turkish industrial production performance and field performance of the country's most popular club, Fenerbahçe SK. It is shown that Fenerbahçe's international wins have a significant effect on the industrial growth where for domestic successes an insignificant effect has been observed. McManus [5] claims that rapid commercialism and commodification of Turkish league football has affected the activities of club supporter groups. A case on Beşiktaş JK, league champion of 2016, implies a change in fan groups' actions moving beyond football, and groups gaining a status as an ethical and political body, especially with support of social media. Other studies on Turkish clubs by means of economical indicators such as liquidity, liability, profitability and stock performance can be found in Berument *et al.* [6] and Ecer and Boyukaslan [7].

This study provides a blueprint for weekly performance assessment of competing teams and an estimation scheme of the final standings at the earliest time horizon in the fixture. Due to its financial implications, a good guess about a team's final standing is important at any point during the league's progress should the team continue to perform as it did until then. This also gives a team the chance of improving its inefficiencies in the rest of the season to attain a better standing. An empirical analysis on Turkish Süper Lig is illustrated by using Data Envelopment Analysis (DEA), a very popular non-parametric frontier estimation technique. It is also shown that a model incorporating expert knowledge performs better.

Rest of the thesis is organized as follows. A review of the existing literature relevant to our work is presented in Chapter 2. Then, Chapter 3 presents the data which we used on our models as inputs and outputs. Later then Chapter 4 describes the methodology and explains mathematical models. Chapter 5 presents the empirical results obtained with DEA analysis and finally Chapter 6 concludes the thesis.

Chapter 2

Literature Review

DEA has been widely used to assess the performance of football related activities with a variety of performance indicators. Haas [8] investigated the technical and scale efficiency of football teams in the English Premier League, took the playing talent and the coaching capabilities available to a team as inputs. The outputs included the points won and total revenues, while taking the population size of the home town as a non-discretionary input. Haas [9] investigated the technical efficiency of soccer teams in the Major League Soccer bearing in the mind that players' wage bill and wage of the head coach as inputs, and points awarded, absolute number of spectators and revenues as outputs. Haas *et al.* [10] studied the efficiency of football teams in the German Bundesliga considering players' wage bill and wage of the head coach as inputs, and points awarded, total revenues and average stadium utilization as outputs.

Bosca *et al.* [11] analyzed offensive and defensive efficiency of Italian and Spanish football teams to shed light on the sport performance. The offensive inputs include shots-on-goal, attacking plays made by the team, balls kicked into the opposing team's goal area and minutes of possession while the defensive inputs are the inverse of the offensive inputs. The offensive output is number of goals scored while the defensive output is the inverse of the number of goals conceded. First, DEA model compares these inputs with the output to establish which team is more efficient. Secondly, using regression analysis the authors explain how the points obtained by the teams correspond to different indicators to decide which one is more important to be efficient offensively or defensively, and to obtain a high ranking in the league.

Espitia-Escuer and Garcia-Cebrian [12] measured the efficiency of the professional soccer teams that play in the Spanish First Division taking the players used, attacking moves, the minutes of possession of the ball and the shots and headers as input variables; as output, they considered the number of points achieved. Espitia-Escuer and Garcia-Cebrian [13] examined the Total Factor Productivity evolution of Spanish First Division Football teams using the Malmquist Index. Garcia-Sanchez [14] applied a three-stage-DEA model to Spanish Professional Football League separating the teams' economic behavior into three components: operating efficiency, athletic or operating effectiveness, and social effectiveness. Guzman and Morrow [15] studied the efficiency of clubs in the English Premier League and used Malmquist non-parametric technique to measure changes in efficiency and productivity. They also used DEA with Canonical Correlation Analysis to ensure the cohesion of the input and output variables.

Soleimani-Damaneh *et al.* [16] utilized input-oriented weight-restricted DEA technique for evaluating the performance of the teams in the Iranian primary football league. They engaged Analytical Hierarchy Process (AHP) for aggregating the subfactors which are involved in input factors, then calculated the efficiency measures with DEA. In addition, with AHP they constructed weight restrictions for increasing the discrimination power of the DEA model. Zambom-Ferraresi *et al.* [17] evaluated the sports performance of teams competing in the UEFA Champions League. They used a bootstrap DEA model considering inputs ad attempts on target, ball possession, total passes and ball recoveries, and sports results as output.

Focusing on match efficiencies rather than teams', Villa and Lozano [18] assess the scoring efficiency of each football match in the season. By averaging these match efficiencies they compute teams' scoring efficiencies for the season and find a virtual final league table as well. Since the proposed DEA models can be run after each match, the changes in efficiency can be monitored throughout the season similar to what we propose in our study. They applied their approach to Spanish First Division teams for one season only. The other articles about football efficiency can be found in Table 2.1.

Several applications of DEA for sport performance evaluation can be found such as Cooper *et al.* [19] for basketball players, Lewis *et al.* [20] for Major League Basketball teams, Amin and Sharma [21] for cricket team selection among others. Articles about DEA for performance evaluation in sports other than football can be found in Table 2.2 through 2.4.

Table 2.1: Review of the literature on performance assessment of football teams using DEA.

Football			
Papers	*Methodology*	*Inputs*	*Outputs*
Ascari Gapnepain [22]	CCR model BCC model	Ball possession Wages Red cards Town population	Goal Shots Points
Barros Garcia-del-Barrio [23]	Bootstrap DEA	Operational cost Team payroll Total assets	Attendance Other receipts
Barros *et al.* [24]	Bootstrap DEA	Operational cost Total assets Team payroll	Attendance Points awarded Total receipts
Barros Leach [25]	CCR model BCC model	Players Wages Net assets Stadium facilities	Turnover Points Attendance
Guzman [26]	DEA Malmquist Poductivity Index	Staff costs General expenses	Turnover
Kounetas [27]	Bootstrap DEA	Total players' transfer expenses and contract renewals Operational costs	Points Total attendance
Picazo-Tadeo Gonzalez-Gomez [28]	DEA	Number of players Attendance (fans)	Points awarded Games played in European competitions and King's Cup
Sala *et al.* [29]	DEA window analysis CCR-O model	Attacks in area centre plays Attacks in area shots on	Goal scored Inverse of goals received

Table 2.2: Review of the literature on performance assessment of basketball and handball teams using DEA.

Basketball			
Papers	*Methodology*	*Inputs*	*Outputs*
Aizemberg *et al.* [30]	BCC model	Payroll Average attendance	Wins Average points per game
Moreno Lozano [31]	Network DEA Black-box DEA	Team budget	Number of team victories
Lee and Berri [32]	Stochastic Frontier Analysis SFA	Team wins	Talent of guards Talent of power forward and centers
Hofler and Payne [33]	SFA	Rebound, Assists Steals, Free throw Blocked shots Percentage of field goal	Team wins (actual number)
Handball			
Papers	*Methodology*	*Inputs*	*Outputs*
Gutiérrez Ruiz [34]	CCR model Cross-efficieny	Constant input	Number of goals scored (9m) Number of goals scored (6m) Fastbreak goals Assists Fouls Number of 7m caused Turnovers

Table 2.3: Review of the literature on performance assessment of tennis and olympic games using DEA.

Tennis			
Papers	*Methodology*	*Inputs*	*Outputs*
Glass *et al.*[35]	VRS Super-efficiency model	First serves in (%) Points won on first serve (%) Points won on second serve (%) Average aces per match Inverse of average double faults per match Break points save (%) Service games won (%) Points won returning the first serve (%) Points won returning the second serve (%) Break points won (%) Returns games won (%) Tie breaks won (%)	Season earnings Matches won (%)
Olympic Games			
Papers	*Methodology*	*Inputs*	*Outputs*
Lozano Villa Cortes [36]	VRS AR	Gross National Product Population	Number of gold medals Number of silver medals Number of bronze medals
Wu Zhou Liang [37]	Integer-valued DEA model	Gross Domestic Product Population	Number of gold medals Number of silver medals Number of bronze medals

Table 2.4: Review of the literature on performance assessment of baseball, handball and golf teams using DEA.

Baseball			
Papers	*Methodology*	*Inputs*	*Outputs*
Anderson Sharp [38]	Composite Batter Index CCR-I model	At-bats Runs-batted-in Fielding average Runs scored Number of seasons played	Number of walks Singles Doubles Triples Home runs
Porter and Scully [39]	LP model	Hitting Pitching	Percentage of wins
Depken [40]	Fixed effects model	Team winning percentage	Salary expenditure Intrateam salary
Kang *et al.*[41]	CCR model	Total player salary	Winning percent Total fan attendance
Cycling			
Papers	*Methodology*	*Inputs*	*Outputs*
Rogge *et al.* [42]	Robust DEA-based efficiency	Number of cycling quotient Team budget Number of tour starts Tour team consistency	CQ points collected Prize money Prizes
Golf			
Fried Lambrinos Tyner [43]	BCC model	Driving distance Drives in fairway Scrambling Greens hit in regulation Sand saves Number of putts per green	Earnings per event

Chapter 3

Data

The data in this study have been collected from the official homepage of the Turkish Professional Football League web site [44] and a private organization FSTATS [45] with detailed statistics of Turkish Süper Lig Football Clubs in the years 2011/12 to 2015/16 (18 Clubs $\times$ 34 weeks $\times$ 5 seasons). Sample data for each season is shown in Tables A.1 through A.5. We begin by defining football's output, and then verify out choice of inputs the analysis of DEA models. Scoring a goal in football is one of the most thrilling moments and determines the winner of the game. Thus, our output is the goal ratio; the number of goals scored divided by the number of goals conceded.

Determining the best performance indicators/variables to use in a DEA analysis is an open question. Furthermore, not all relevant data may be available publicly, or they may not even be collected so the researchers are restricted to data they can obtain. In addition, data sets involving football performance usually contain vast amounts of statistics and indicators belonging to each team. DEA faces a challenge when working with such a high number of performance indicators compared to relatively small number of decision making units. Drake and Howcroft [46] overcome this by stating a critical ratio in a rule of thumb manner as the number of the inputs and outputs should at least be twice greater than the decision units under investigation. Since we have a small number of decision making units, a correlation analysis has been performed in order to identify truly effective performance indicators and to eliminate redundancies. Resulting matrix containing the pairwise Pearson correlation coefficient shown in Table A.6 allows us to refine the inputs into a smaller subset. For example, number of assists and goal positions are highly correlated to each other with a correlation coefficient 0.82. A further elimination is done for the performance indicator free kicks. Although it could not be eliminated immediately due to low correlations with other variables, it was eliminated after applying the methodology explained in the study because it did not change the efficiency results at all.

Some researchers such as Haas *et al.* [10] have used data involving the economic value of each team in their team efficiency studies. Several resources for such data come to mind. One is transfer money paid to players. This money is agreed upon before the season starts and stays the same throughout the season. Thus, since we are trying to estimate final league standings after each week, transfer fees data cannot be used towards that end. Another financial indicator could have been stock values of the teams which actually change over time but most Turkish football clubs are not public. Attendance numbers also have financial implications and they have been used by other researchers such as Haas [9]. But in Turkey fans of teams have long been banned from away games by local authorities making such data irrelevant to our study. Nevertheless, in Section 5 we also give our findings obtained using transfer money data together with other data for the whole season in a static manner.

After this initial analysis of the data at hand, the number of goal positions, the number of shots on target, the number of crosses on target, the number of corner kicks and the ball possession percentage were our chosen inputs.

- Goal positions: This indicator is naturally related to the number of goals a team scores. In general, teams that perform better in the season produce more goal positions. The number of goal positions a team creates physically tires and psychologically demoralizes opposing teams.

- Shots on target: A shot is an attempt that is taken with the purpose of scoring and is directed toward the goal. A shot on target either results in a save by the goalkeeper/defending team, or a goal by the attacking team.

- Crosses on target: A cross is a high ball sent into the goal area with different intensities. The most common cross is a ball sent from the corner lines towards the area in front of the goal. A good cross generates a threat for the opposing team because the fast incoming ball can be sent via foot or head into the goal without the defenders being able to react quickly enough.

- A corner kicks: A corner kick is awarded to the attacking team when the ball leaves the field of play by crossing the goal line either on the ground or in the air without a goal having been scored, having been last touched by a defending player. The kick is taken from the corners of the field nearest to where the ball crossed the goal line. Corner kicks are considered to be a reasonable goal scoring opportunity for the attacking side. It is even possible to score directly from a corner kick if sufficient swerve is given to the kick.

- Ball possession: Ball possession is the percentage of total game time where a team has the control of the ball. A high ball possession shows that a team dominates the game winning the match with a high likelihood.

The descriptive statistics of selected input and output variables for all analyzed seasons are provided in Table 3.1.

Table 3.1: Descriptive statistics.

		Inputs					Output
Season		Goal positions	Shots on target	Crosses on target	Corner kicks	Ball possession	Goal Ratio
2011-2012	Max	198	218	227	188	56	2.88
	Min	95	108	111	133	41	0.29
	Average	153.94	164.17	166.33	162.06	48.28	1.10
	SD	29.64	29.21	31.01	15.89	4.07	0.56
2012-2013	Max	197	202	207	227	57	1.89
	Min	114	101	122	129	45	0.58
	Average	157.50	159.83	148.72	165.61	49.39	1.03
	SD	24.12	26.34	22.34	24.86	3.93	0.32
2013-2014	Max	223	235	184	211	56	2.24
	Min	142	127	101	137	45	0.53
	Average	165.61	166.06	138.94	170	49.50	1.07
	SD	23.56	25.95	24.73	19.12	3.47	0.46
2014-2015	Max	229	223	210	217	58	2.07
	Min	126	136	104	114	40	0.65
	Average	165.06	171.72	135.39	160.89	49.56	1.09
	SD	32.01	25.68	27.93	26.48	3.94	0.45
2015-2016	Max	226	220	165	221	57	2.22
	Min	103	124	73	120	46	0.44
	Average	156.33	158.67	102.22	162.72	49.56	1.09
	SD	33.54	29.31	25.90	27.84	3.38	0.51

Max= maximum; Min= minimum; SD= standard deviation.

Chapter 4

Methodology

Our methodology proceeds as follows. First, via DEA we find team efficiencies by utilizing the data through the week that has just been played. These team efficiencies are then used to predict final league standings of the teams. The predictions are dynamically renewed after each week. While we report results via a standard DEA model as well, we find out that a model that uses expert knowledge makes better predictions. To collect expert opinion, we use Analytic Hierarchy Process (AHP).

4.1 Data Envelopment Analysis (DEA)

Data Envelopment Analysis (DEA) first introduced by Charnes [47] is an optimization technique for evaluating the comparative efficiency of homogenous decision making unit (DMU), consuming inputs and transforming them into outputs. The term comparison is used because the evaluation is carried out relative to the DMUs present in the peer set. This comparison is performed by finding the efficiency of each DMU with respect to other DMUs with most efficient DMUs setting benchmarks.

We used Charnes, Cooper and Rhodes (CCR) input-oriented model (Cooper *et al.* [48]) for evaluating the efficiency of football teams (DMUs). This model aims to minimize inputs (or resources consumed) while satisfying at least the given input levels. There exist several other DEA models that are actually variants of the original version given below. Let n be the number of DMUs, m be the number of inputs and s be the number of outputs. Let us assume that we have a data matrix containing the input and output values of DMUs with a size of n by m+s.

Then the fractional CCR model is formulated as below.

$$\max \quad \theta = \frac{\sum_{r=1}^{s} u_r y_{r_0}}{\sum_{i=1}^{m} v_i x_{i_0}} \tag{4.1}$$

subject to:

$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1 \quad j = 1, ..., n \tag{4.2}$$

$$u_r, v_i \geq 0 \quad r = 1, ..., s; i = 1, ..., m \tag{4.3}$$

DEA model evaluates the efficiency score, θ, of DMU j_0 with reference to all other *n-1* DMUs where x_{ij} and y_{rj} are the relevant input and output levels of DMU under evaluation from the data matrix. The positive weights of inputs and outputs are decision variables, and represented by u_r and v_i.

As solving the fractional is difficult, it was converted to a linear programming (LP) model by Charnes *et al.* [47]:

$$\max \quad \theta = \sum_{r=1}^{s} u_r y_{r_0} \tag{4.4}$$

subject to:

$$\sum_{i=1}^{m} v_i x_{i_0} = 1 \tag{4.5}$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0 \quad j = 1, ..., n \tag{4.6}$$

$$u_r, v_i \geq 0 \quad r = 1, ..., s; i = 1, ..., m \tag{4.7}$$

We illustrate a small numerical example of the CCR model (LP form).

The data for 2015-2016 season is shown in Table A.5. There are 18 DMUs with 5 inputs and 1 output. The following formulation belongs to team Fenerbahçe.

max θ = 2.222u

subject to:

2.222u-221v_1-203v_2-165v_3-219v_4-56v_5 ≤ 0

1.024u-132v_1-136v_2-77v_3-120v_4-47v_5 ≤ 0

1.000u-162v_1-162v_2-84v_3-164v_4-50v_5 ≤ 0

1.500u-157v_1-163v_2-104v_3-151v_4-50v_5 ≤ 0

2.143u-226v_1-220v_2-116v_3-221v_4-57v_5 ≤ 0

0.855u-149v_1-148v_2-128v_3-151v_4-50v_5 ≤ 0

0.813u-150v_1-145v_2-118v_3-152v_4-46v_5 ≤ 0

0.619u-1311v_1-144v_2-76v_3-146v_4-47v_5 ≤ 0

1.408u-206v_1-207v_2-119v_3-170v_4-55v_5 ≤ 0

0.620u-103v_1-124v_2-73v_3-124v_4-47v_5 ≤ 0

1.000u-133v_1-131v_2-89v_3-148v_4-46v_5 ≤ 0

1.250u-176v_1-186v_2-117v_3-174v_4-50v_5 ≤ 0

0.610u-139v_1-137v_2-83v_3-181v_4-48v_5 ≤ 0

1.333u-133v_1-131v_2-77v_3-135v_4-48v_5 ≤ 0

0.437u-119v_1-126v_2-83v_3-155v_4-48v_5 ≤ 0

1.440u-167v_1-177v_2-80v_3-189v_4-46v_5 ≤ 0

0.708u-163v_1-150v_2-115v_3-178v_4-51v_5 ≤ 0

0.678u-147v_1-166v_2-136v_3-151v_4-50v_5 ≤ 0

221v_1+203v_2+165v_3+219v_4+56v_5=1

u,v_1,v_2,v_3,v_4,v_5 ≥ 0

The computational effort of linear programming is prone to grow in proportion to powers of the number of constraints. The number of DMUs, n, is quite larger than $(m + s)$, the number of inputs and outputs and therefore it takes more time to solve LP which has n constraints than to solve dual problem which has $(m + s)$ constraints. Moreover, the interpretations of dual problem are more comprehensible because the solutions are characterized as inputs and outputs that correspond to the original data whereas the multipliers provided by solution to LP represent evaluations of these observed values. These values are also important, they are generally best reserved for supplementary analysis after a solution to dual problem is achieved [48]. The dual of CCR model is:

$$\min \quad \theta \tag{4.8}$$

subject to:

$$\sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta_0 x_{i_0} \quad i = 1, ..., m \tag{4.9}$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{r_0} \quad r = 1, ..., s \tag{4.10}$$

$$\lambda_j \geq 0 \quad j = 1, ..., n \tag{4.11}$$

The dual is illustrated below by a numerical example for team Fenerbahçe.

min θ

subject to:

$132\lambda_1+162\lambda_2+157\lambda_3+226\lambda_4+149\lambda_5+150\lambda_6+131\lambda_7+221\lambda_8+206\lambda_9+103\lambda_{10}+133\lambda_{11}$
$+176\lambda_{12}+139\lambda_{13}+133\lambda_{14}+119\lambda_{15}+167\lambda_{16}+163\lambda_{17}+147\lambda_{18} \leq 211\theta$

$136\lambda_1+162\lambda_2+163\lambda_3+220\lambda_4+148\lambda_5+145\lambda_6+144\lambda_7+203\lambda_8+207\lambda_9+124\lambda_{10}+131\lambda_{11}$
$+186\lambda_{12}+137\lambda_{13}+131\lambda_{14}+126\lambda_{15}+177\lambda_{16}+150\lambda_{17}+166\lambda_{18} \leq 203\theta$

$77\lambda_1+84\lambda_2+104\lambda_3+116\lambda_4+128\lambda_5+118\lambda_6+76\lambda_7+165\lambda_8+119\lambda_9+73\lambda_{10}+89\lambda_{11}+117\lambda_{12}$
$+83\lambda_{13}+77\lambda_{14}+83\lambda_{15}+80\lambda_{16}+115\lambda_{17}+136\lambda_{18} \leq 165\theta$

$120\lambda_1+164\lambda_2+151\lambda_3+221\lambda_4+151\lambda_5+152\lambda_6+146\lambda_7+219\lambda_8+170\lambda_9+124\lambda_{10}+148\lambda_{11}$
$+174\lambda_{12}+181\lambda_{13}+135\lambda_{14}+155\lambda_{15}+189\lambda_{16}+178\lambda_{17}+151\lambda_{18} \leq 219\theta$

$47\lambda_1+50\lambda_2+50\lambda_3+57\lambda_4+50\lambda_5+46\lambda_6+47\lambda_7+56\lambda_8+55\lambda_9+47\lambda_{10}+46\lambda_{11}+50\lambda_{12}+48\lambda_{13}$
$+48\lambda_{14}+48\lambda_{15}+46\lambda_{16}+51\lambda_{17}+50\lambda_{18} \leq 56\theta$

$1.024\lambda_1+1.000\lambda_2+1.500\lambda_3+2.143\lambda_4+0.855\lambda_5+0.813\lambda_6+0.619\lambda_7+2.222\lambda_8+1.408\lambda_9$
$+0.620\lambda_{10}+1.000\lambda_{11}+1.250\lambda_{12}+0.610\lambda_{13}+1.333\lambda_{14}+0.437\lambda_{15}+1.440\lambda_{16}+0.708\lambda_{17}$
$+0.678\lambda_{18}\geq 2.222$

$\lambda_1+\lambda_2+\lambda_3+\lambda_4+\lambda_5+\lambda_6+\lambda_7+\lambda_8+\lambda_9+\lambda_{10}+\lambda_{11}+\lambda_{12}+\lambda_{13}+\lambda_{14}+\lambda_{15}+\lambda_{16}+\lambda_{17}+\lambda_{18}\geq 0$

After writing all these equations for each team (DMUs), then we solved CCR model for 2015-2016 season by using DEA-Solver Pro [49]. The results of this example are shown in Table 4.1. There are three efficient teams which are Beşiktaş, Fenerbahçe and Konyaspor and the rest are inefficient teams. By looking at the efficiency scores for all DMUs, we can understand how much inefficient units need to reduce their inputs or increase their outputs to become efficient. The efficiency graph is shown in Figure 4.1 .

In CCR model, the optimal weights (u_r^*, v_i^*) for inefficient DMUs may result in many zeros implying weakness in the corresponding items compared with efficient DMUs. Additionally from Table 4.1 one can see that two important inputs in football, shots on target and number of corner kicks, have zero weights for almost all teams. To get rid of zero weights which frequently appear in CCR model, we used the Assurance Region (AR) model developed by Thompson *et al.* [50]. In AR model, lower and upper bounds are set for ratios of input and output variables. Thus, the model has the following additional constraints over CCR model.

$$lb_{i,i'} \leq \frac{v_i}{v_{i'}} \leq ub_{i,i'} \quad i = 1, ..., m; i\,' = 1, ..., m; i \neq i\,'; i < i\,' \tag{4.12}$$

$$LB_{r,r'} \leq \frac{u_r}{u_{r'}} \leq UB_{r,r'} \quad r = 1, ..., s; r\,' = 1, ..., s; r \neq r\,'; r < r\,' \tag{4.13}$$

where $lb_{i,i'}$ ($ub_{i,i'}$) are lower (upper) bounds on the ratios of input weights and $LB_{r,r'}$ ($UB_{r,r'}$) are the lower (upper) bounds on the ratios of output weights.

Table 4.1: Results of a numerical example from 2015-2016 season.

Teams	Score	V(1)	V(2)	V(3)	V(4)	V(5)	(U1)
Akhisar Belediyespor	0.85	0.00	0.00	0.04	0.02	0.00	0.83
Antalyaspor	0.65	0.12	0.00	0.18	0.00	0.00	0.65
Başakşehir	0.99	0.00	0.00	0.03	0.20	0.00	0.66
Beşiktaş	1.00	0.08	0.00	0.13	0.00	0.00	0.47
Bursaspor	0.57	0.23	0.00	0.00	0.00	0.00	0.67
Çaykur Rizespor	0.54	0.23	0.00	0.00	0.00	0.00	0.66
Eskişehirspor	0.47	0.19	0.00	0.06	0.00	0.00	0.77
Fenerbahçe	1.00	0.15	0.00	0.00	0.00	0.00	0.45
Galatasaray	0.82	0.00	0.00	0.03	0.18	0.00	0.58
Gaziantepspor	0.60	0.33	0.00	0.01	0.00	0.00	0.97
Gençlerbirliği	0.75	0.25	0.00	0.01	0.00	0.00	0.75
Kasımpaşa	0.72	0.00	0.00	0.04	0.16	0.00	0.57
Kayserispor	0.44	0.18	0.00	0.06	0.00	0.00	0.72
Konyaspor	1.00	0.25	0.00	0.01	0.00	0.00	0.75
Mersin İdmanyurdu	0.36	0.28	0.00	0.01	0.00	0.00	0.84
Osmanlıspor	0.98	0.00	0.00	0.43	0.00	0.00	0.68
Sivasspor	0.44	0.00	0.17	0.07	0.00	0.00	0.62
Trabzonspor	0.46	0.23	0.00	0.00	0.00	0.00	0.68

V(1);V(2);V(3);V(4);V(5) are the weights of the inputs, U(1) is the weight of the output.

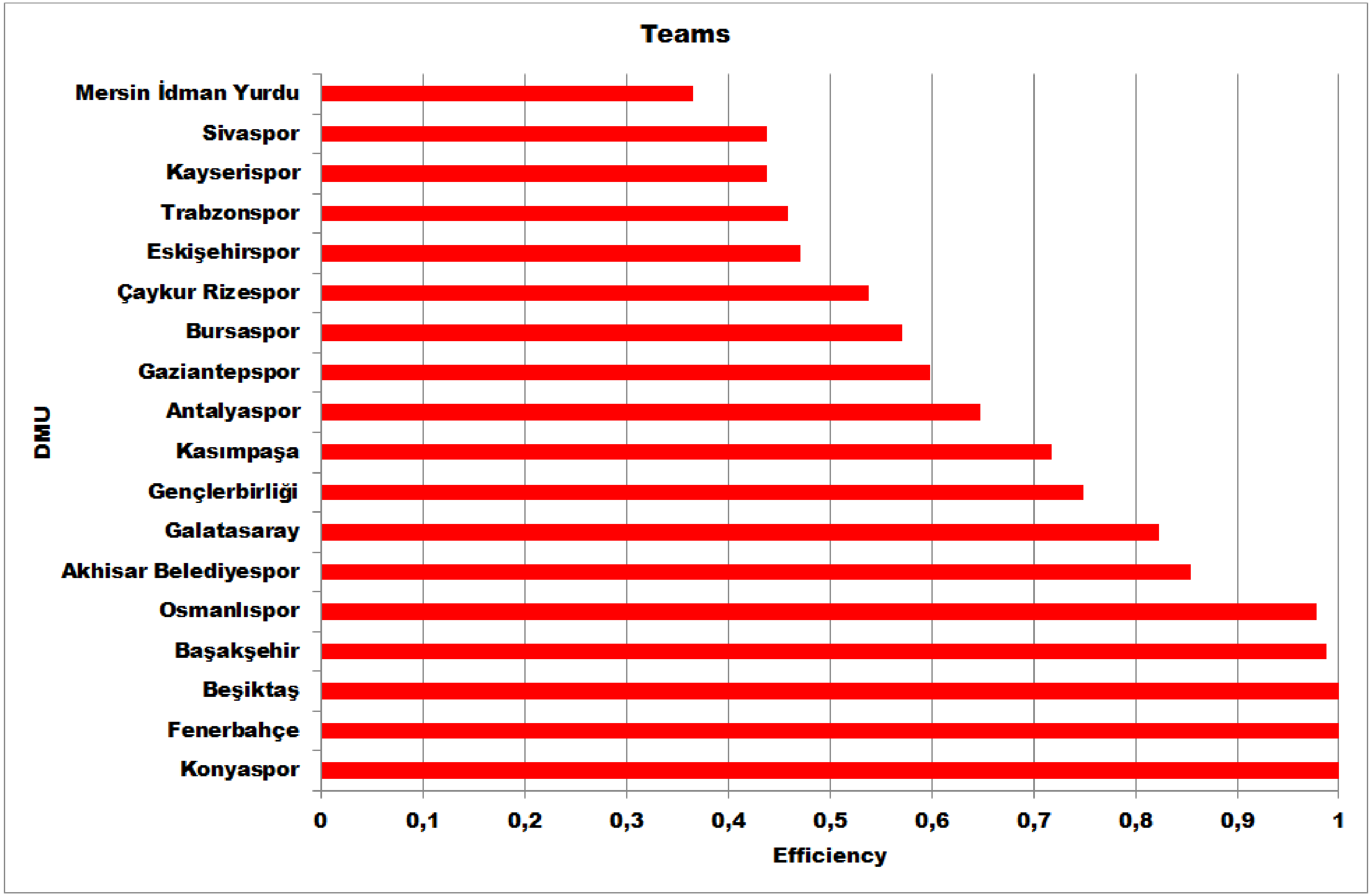

Figure 4.1: Efficiency graph of 2015-2016 season.

4.2 Analytic Hierarchy Process (AHP)

To determine AR bound values we used Analytic Hierarchy Process (AHP) which was developed by Saaty [51] to deal with complex decision making. AHP may help the decision maker to set priorities and make the best decision by reducing complex decisions to a series of pairwise comparisons and then synthesizing the results. Moreover, AHP is a practical technique for checking the consistency of the decision makers' pairwise comparisons of the criteria. AHP is conducted through a questionnaire answered by area experts. Example questionnaire is shown in Figure A.1.

In this study, the questionnaire was administered to five football players to identify their expert opinion about relative importance of criteria that affect team performances. Respondents were asked to conduct pairwise comparisons among the input variables on a 1 to 9 scale as in Saaty [52].

The nine-point scale is shown in Table 4.2.

Table 4.2: Saaty's nine-point scale for relative importance.

Importance Level	Definition	Explanation
1	Equal importance	Two criteria play a role equally
3	Moderate importance	Judgement slightly support one criterion over another
5	Strong importance	Judgement strongly support one criterion over another
7	Very strong importance	Judgement is supported very strongly over another
9	Extreme importance	The argument supporting one criterion over another
2,4,6,8	Intermediate values	When compromise is between two adjacent needed judgement

The first step is the pairwise comparison for the inputs by five experts shown in Table A.7 through A.11. Then, we calculate the geometric mean of pairwise comparison matrix for the inputs by five experts shown in Table 4.3.

Table 4.3: Geometric mean matrix.

	Goal Positions	Shots on Target	Crosses on Target	Corner Kicks	Ball Possession
Goal Positions	1.0000	1.4768	4.5844	8.0018	5.0776
Shots on Target	0.6776	1.0000	7.7403	8.1393	1.8384
Crosses on Target	0.2181	0.1292	1.0000	2.7131	1.6345
Corner Kicks	0.1250	0.1229	0.3505	1.0000	0.2717
Ball Possession	0.1969	0.5439	0.6118	3.6801	1.0000
SUM	**2.2177**	**3.2718**	**14.2870**	**23.5343**	**9.8222**

The second step is to normalize the matrix by totaling numbers in each column. Each entry in the column is divided by the column sum to yield its normalized scores shown in Table 4.4. The sum of each column should be 1.

Table 4.4: Normalized matrix.

	Goal Positions	Shots on Target	Crosses on Target	Corner Kicks	Ball Possession	Average
Goal Positions	0.4509	0.4511	0.3209	0.3400	0.5169	**0.4160**
Shots on Target	0.3056	0.3056	0.5418	0.3458	0.1872	**0.3372**
Crosses on Target	0.0984	0.0395	0.0700	0.1153	0.1664	**0.0979**
Corner Kicks	0.0564	0.0376	0.0245	0.0425	0.0277	**0.0377**
Ball Possession	0.0888	0.1663	0.0428	0.1564	0.1018	**0.1018**

The third step is to calculate the Consistency Ratio (CR). If the CR is much in excess of 0.1, then the questionnaires are inconsistent. For CR calculations, there are two steps:

- Calculate the Consistency Index (CI).

- Calculate the Consistency Ratio.

$$CR = \frac{CI}{RI} \quad and \quad CI = \frac{\lambda_{max} - n}{n-1} \tag{4.14}$$

where n is the number of inputs. Random Index (RI) is the average random consistency index found using a large sample of randomly generated reciprocal matrices with scales 1/9, 1/8,..., 1,..., 8, 9. As calculated by Saaty [51], the number of the inputs and the average RI are shown in Table A.12.

For the calculation of the consistency index, first, we find λ_{max} as follows. For our first input (goal positions) we first need to calculate its λ value by multiplying geometric means with normalized scores.

λ_{input1}:

(1.0000*0.4160)+(1.4768*0.3372)+(4.5844*0.0979)+(8.0018*0.0377)+(5.0776*0.1018) = 2.2289

Then $\lambda_{input1} = 2.2289/0.4160 = 5.3585$.

We calculate all λ values the same way; the values are given below:

$$\lambda_{inputs} = \begin{bmatrix} 5.3585 \\ 5.6001 \\ 5.2735 \\ 5.1876 \\ 5.1726 \end{bmatrix}$$

and λ_{max}= 5.3185 is the average of these λ values.

Then,

$$CI = \frac{5.3185 - 5}{5 - 1} = 0.07962. \tag{4.15}$$

$$CR = \frac{CI}{RI} = \frac{0.07962}{1.12} = 0.07. \tag{4.16}$$

In AHP studies, the judgements obtained from the questionnaires are considered inconsistent if the CR is much in excess of 0.1. Our CR is 0.07, thus, our study is consistent.

AHP results helped setting the upper and lower bounds in the AR model. The results are shown in Table 4.5. In this table, weights for each of the input variables are computed in the DEA model. To find lower and upper bound values, the minimum and largest values of each weight for all experts are found. For number of goal positions (I1), the minimum and maximum priority among all experts are 0.2875 and 0.4923, respectively. For number of shots on target (I2), the minimum and the maximum priority among experts are 0.1529 and 0.5156, respectively. Let v_{I1},...,v_{I5} be the weights for input I1,...,I5 respectively. The ratio v_{I1}/v_{I2} has a lower bound of 0.5576 (0.2875/0.5156) and an upper bound of 3.2202 (0.4923/0.1529). In that vein, AR bounds for each pair of inputs can be calculated, as shown in Table 4.6. More information about AR bound calculations can be found in Cooper *et al.* [48].

Table 4.5: Priorities of the inputs by the experts.

	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Minimum priority	Maximum priority
Goal positions (I1)	0.4313	0.4923	0.2875	0.3604	0.3018	**0.2875**	**0.4923**
Shots on target (I2)	0.1529	0.3388	0.3733	0.3093	0.5156	**0.1529**	**0.5156**
Crosses on target (I3)	0.0823	0.0599	0.1724	0.2133	0.0698	**0.0599**	**0.2133**
Corner kicks (I4)	0.0352	0.0492	0.0313	0.0321	0.0380	**0.0313**	**0.0492**
Ball possession (I5)	0.2983	0.0599	0.1356	0.0849	0.0748	**0.0599**	**0.2983**

Table 4.6: Assurance Region lower and upper bounds for input ratios.

Input ratio	**Lower bound**	**Upper bound**
v_{I1}/v_{I2}	0.5576	3.2202
v_{I1}/v_{I3}	1.3474	8.2178
v_{I1}/v_{I4}	5.8479	15.7495
v_{I1}/v_{I5}	0.9636	8.6065
v_{I2}/v_{I3}	0.7166	8.6065
v_{I2}/v_{I4}	3.1100	16.4944
v_{I2}/v_{I5}	0.5124	8.6065
v_{I3}/v_{I4}	1.2187	6.8254
v_{I3}/v_{I5}	0.2008	3.5614
v_{I4}/v_{I5}	0.1048	0.8206

Chapter 5

Results

In this section we present and discuss the results of this study. We experimented with two different DEA models (input-oriented CCR model and AR model) by using DEA-Solver Pro [49] for the weekly assessment of team performances. After each week, an estimate about the final league standings of each team was made from the ranking of the teams' DEA efficiency score obtained by using the season data through that week. Then, we found Pearson correlation coefficients between final league standings (rank) and DEA efficiency ranks of teams by using Minitab [53]. The results of Pearson correlation coefficients (R-square) for each season can found in Appendix A.13 and A.14.

Figure 5.1 shows Pearson correlation coefficients (R-square) between DEA ranks and the final league standings after each week for each season. Moreover, the summary of regression study for CCR and AR models for all seasons are shown in Table 5.1. We can observe that the AR model provides better accuracy than the CCR model. While the correlations are relatively low at the beginning of the season, since they are increasing with time, we could say that a team's chance of placing in the estimated position becomes more and more likely as weeks go by. Looking at the average of maximum number of efficient teams within each season, 5 teams are considered relatively efficient with CCR but with AR this reduces to 3 teams. Average efficiency scores of AR are also better for all seasons. For instance in the 2014-2015 season, the average is 38.45 for CCR and 47.55 for AR. CCR model generates many zero weights for the selected input variables which may not be reasonable in the context of football when evaluating team's efficiency relative to its peer. In the AR model, however, model does not allow such inconsistency to happen thus letting all performance indicators to contribute to the efficiency.

In another experiment, we correlated weekly DEA results with the standing table that realized after each week as seen in Figure 5.2. In the figure, we can compare these results against the final league standing estimations. It is clear that weekly DEA efficiency scores are highly correlated to the immediate league table after the week. However, it is not possible to use early league data for predicting the final table. The more time passes in the league, the better are the final table estimations. This comparison shows that the data cannot be used to predict positions for the weeks too far into the future.

Figure 5.3 provides the progress of the efficiency scores over time four different cases. Here, horizontal axis represents the weeks while vertical axis represents the DEA scores of the AR model. In Graph (a), we show weekly efficiency scores of the top three teams in the final league table and bottom three teams which are relegated to the league in 2013−2014 season. The final team rankings are shown in parentheses next to a team's name. For top teams in the final league table, the efficiency scores are increasing and approaching 1 as weeks pass. On the contrary, for relegated teams efficiency scores are decreasing with time. As another observation, in each of the analyzed seasons, the relegated teams finished the league with an efficiency score under 0.6.

The progress of the efficiency scores of Konyaspor, in Graph (b) reflects the stellar performance of the team in 2015−2016. In that season, Konyaspor had its best ever finish by placing as the 3rd best team with the highest number of points collected by the team. However, in the first half of the season, Konyaspor had only 7 wins and 5 draws in 17 games. Then, in the second half they won 12 out 17 games with one loss only. As can be seen from Graph (b) in Figure 5.3, the efficiency scores for Konyaspor are increasing with time eventually becoming 1.

The efficiency scores of bottom six teams in season 2012−2013 (Elazığspor, Akhisar Belediye Gençlik Spor, Kardemir Karabükspor, Medipol Başakşehir FK, Orduspor and Mersin İdmanyurdu) are shown in Graph (c). The dotted lines belong to the relegated teams. While the efficiency scores at the end of the season are similar in value, teams that were not relegated consistency improved on their scores whereas the scores of relegated teams kept on decreasing with time.

Graph (d) sheds light to the changes in performance of a single team in different seasons. Kayserispor finished in the eleventh position in 2011−2012, then finished 5^{th} in 2012−2013. Then, in 2013−2014 they were relegated. The efficiency scores from these three seasons mirror the changing performance.

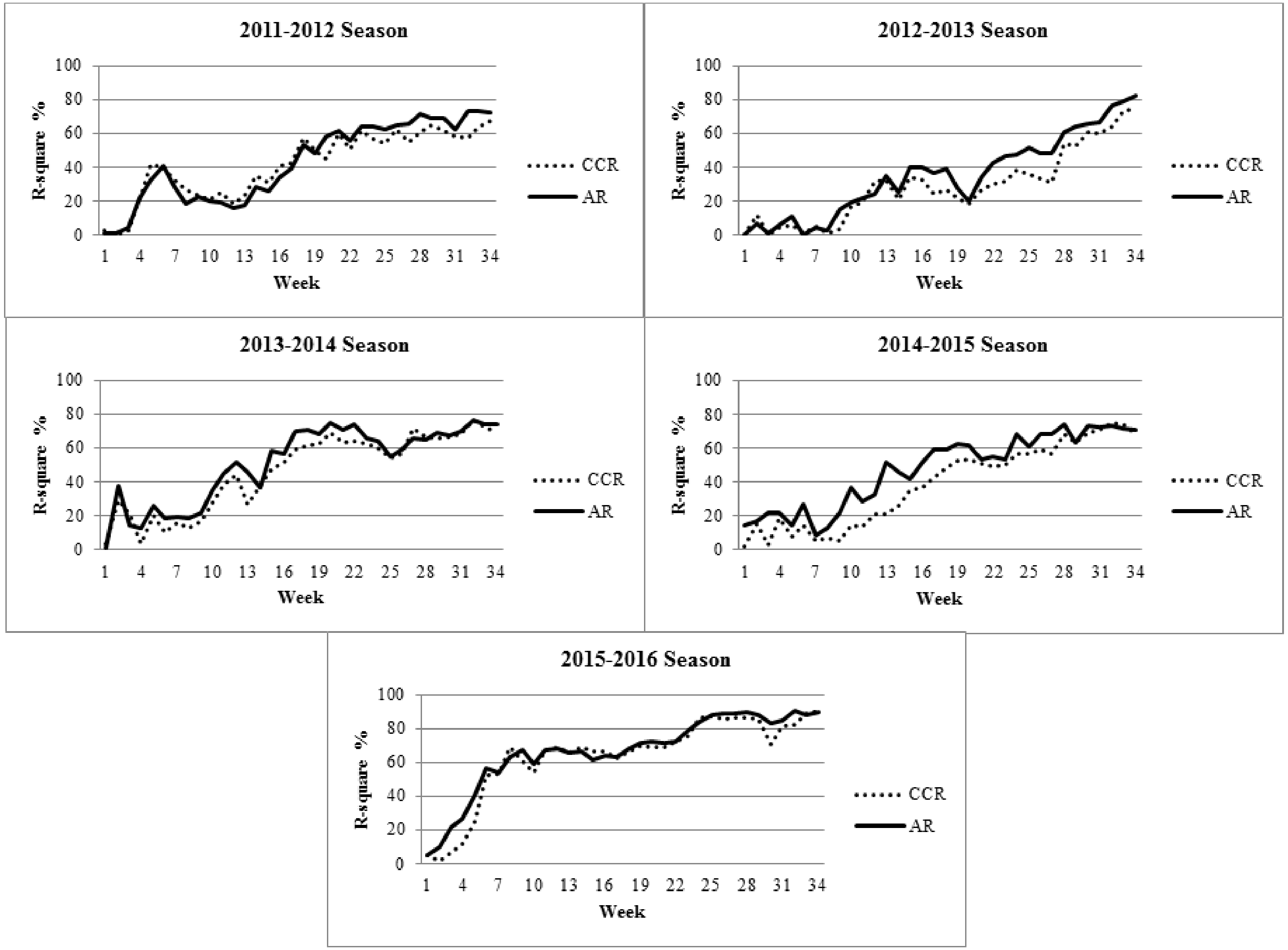

Figure 5.1: Regression on rank: Final league standings vs. DEA estimations.

Table 5.1: Descriptive statistics of CCR and AR models.

Season		CCR	AR
2011-2012	Maximum	68	73
	Minimum	-	1
	Average	41.58	42.89
	Standard deviation	19.60	23.58
	Average number of efficient team	2	1
	Maximum number of efficient team	6	3
2012-2013	Maximum	75	82
	Minimum	-	-
	Average	28.72	34.99
	Standard deviation	21.31	24.26
	Average number of efficient team	2	1
	Maximum number of efficient team	4	3
2013-2014	Maximum	76	77
	Minimum	3	1
	Average	46.32	50.90
	Standard deviation	22.83	22.53
	Average number of efficient team	3	2
	Maximum number of efficient team	6	3
2014-2015	Maximum	74	75
	Minimum	2	8
	Average	38.45	47.55
	Standard deviation	24.28	21.50
	Average number of efficient team	2	1
	Maximum number of efficient team	3	2
2015-2016	Maximum	91	91
	Minimum	2	5
	Average	63.54	66.44
	Standard deviation	24.96	22.57
	Average number of efficient team	2	1
	Maximum number of efficient team	4	4

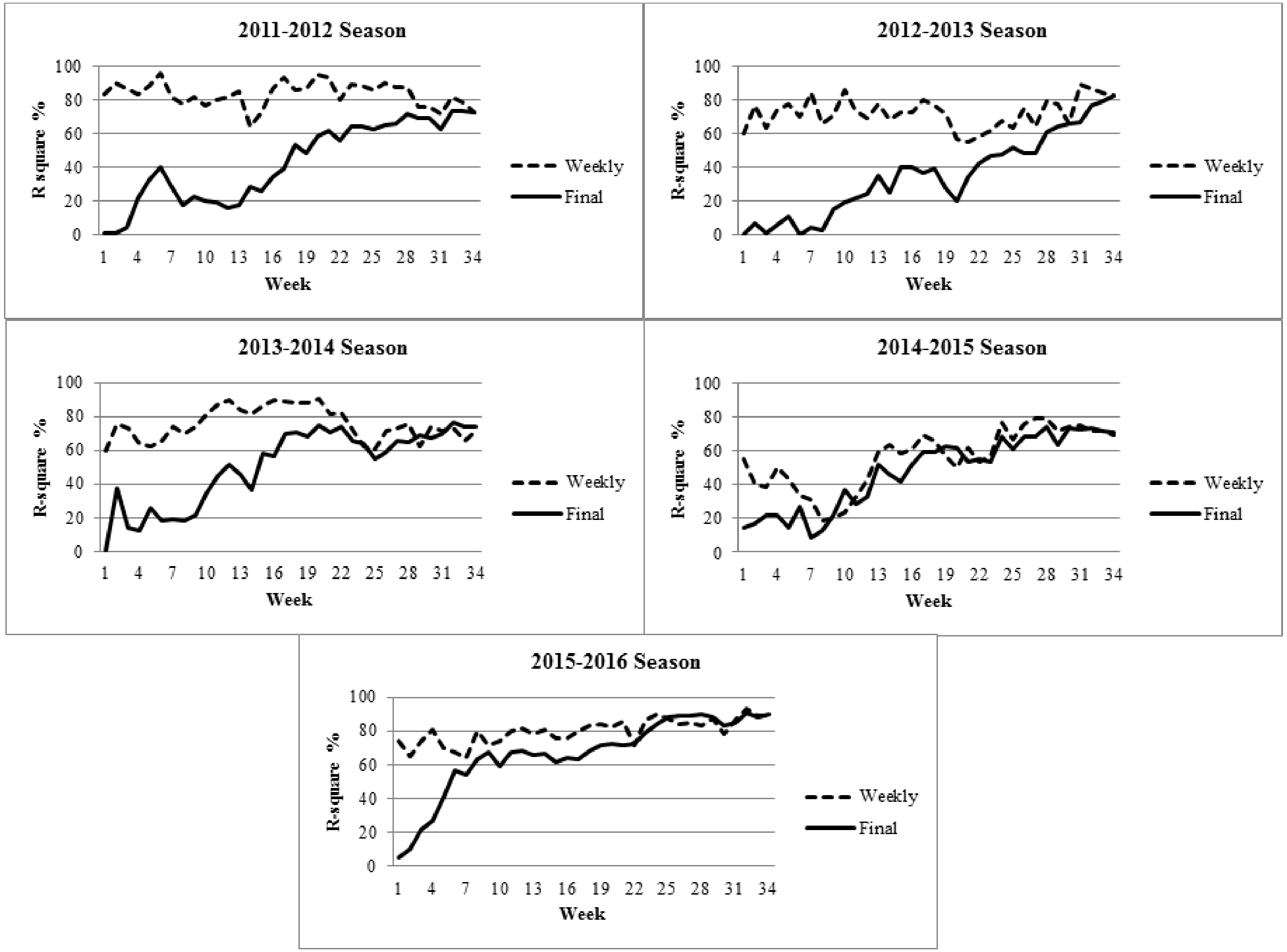

Figure 5.2: Weekly vs. final league rank estimation.

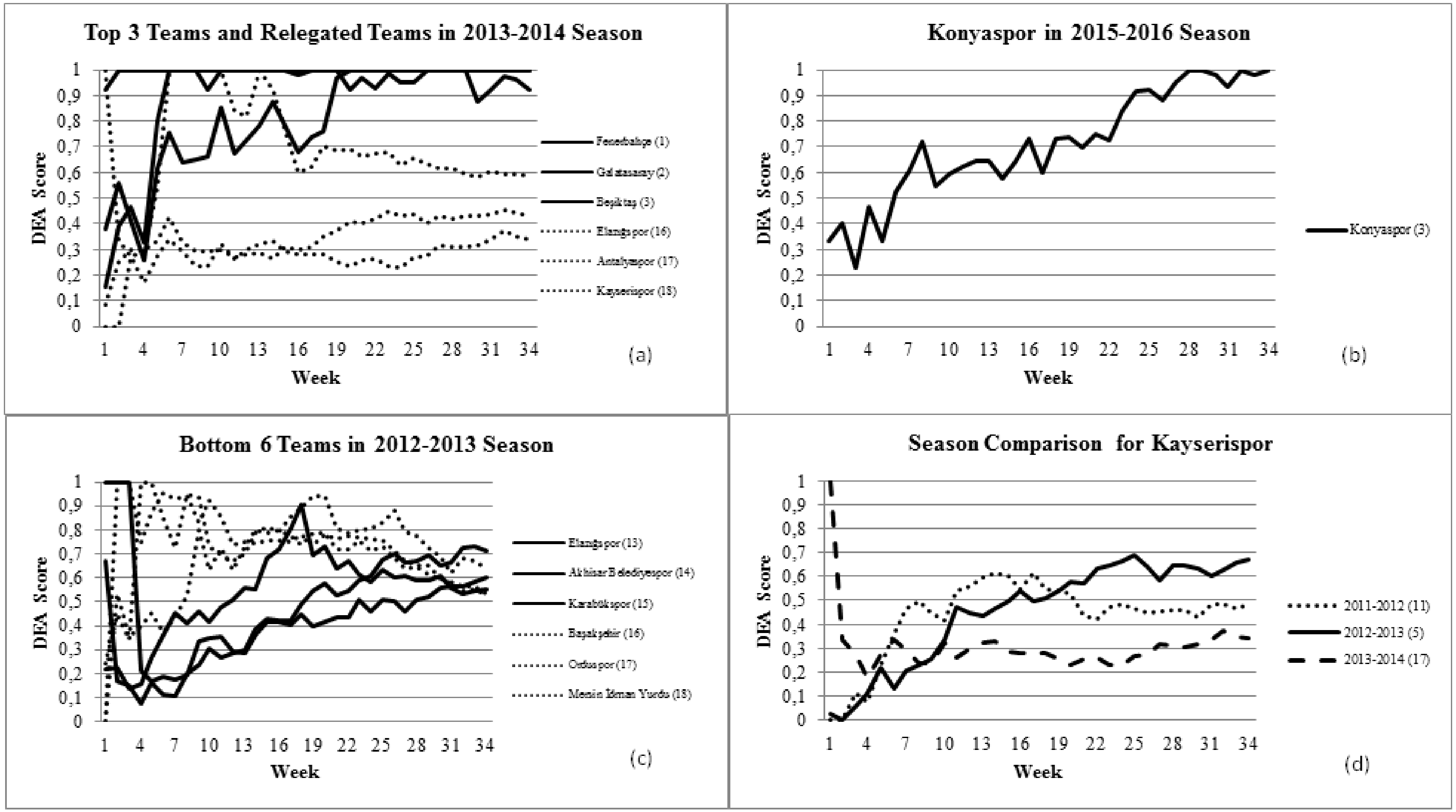

Figure 5.3: Progress of DEA scores for various cases.

5.1 Financial Data

We also had the transfer fee data which have been collected from Transfermarkt web site [54] spent by each team in each season as summarized in Table 5.2. Due to the static nature of the financial data available, it could not be used in our dynamic estimation approach explained earlier. However, we used whole season's data together with this financial data and correlated the results with the final standings. Consolidated results of the financial analysis of five seasons are shown in Figure 5.4. There is an obvious kink in 2013−2014 with correlations becoming better with each season after that. Interestingly, UEFA introduced Financial Fair Play Regulations in 2013−2014 in order to prevent professional football clubs from getting into financial problems by spending more than they earn which might threaten long term survival. It appears that the clubs started using their money wisely after the regulations rather than spending it inefficiently as before.

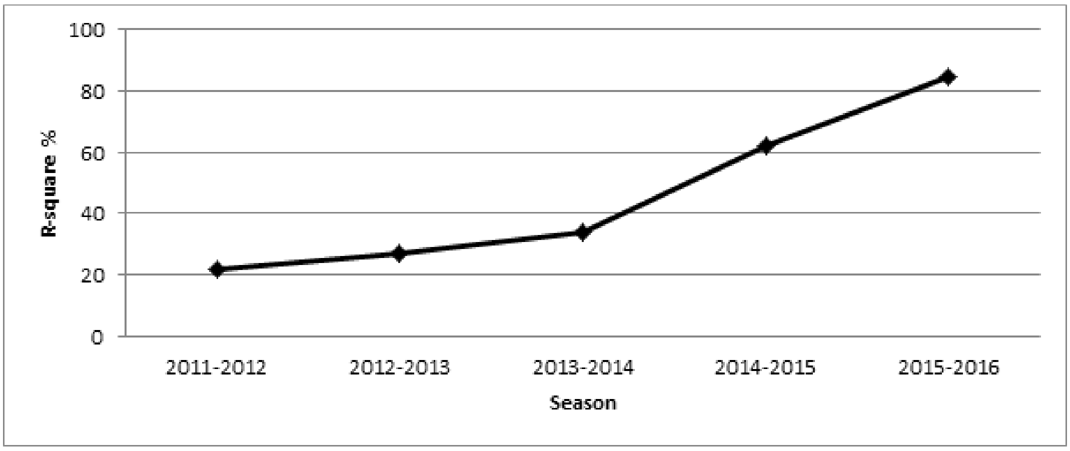

Figure 5.4: Financial analysis of football teams for five seasons.

Table 5.2: Descriptive statistics of financial data.

Season		Transfer Fee (Euro)
2011-2012	Maximum	125,350,000
	Minimum	15,930,000
	Average	49,373,000
	Standard Deviation	35,000,000
2012-2013	Maximum	178,700,000
	Minimum	11,950,000
	Average	59,770,000
	Standard Deviation	45,770,000
2013-2014	Maximum	178,230,000
	Minimum	14,150,000
	Average	59,060,000
	Standard Deviation	45,200,000
2014-2015	Maximum	177,480,000
	Minimum	21,150,000
	Average	56,600,000
	Standard Deviation	41,020,000
2015-2016	Maximum	195,380,000
	Minimum	22,700,000
	Average	69,920,000
	Standard Deviation	47,410,000

Chapter 6

Conclusion

Performance assessment and control of professional football teams are the key elements for success on the pitch. Managerial teams consisting of a head coach, assistant coaches, fitness trainers, physiotherapists, and analysts try to develop different strategies for every opponent they face in the national or international contest they appear throughout the season. Most important resource at hand is such strategy planning is the player roster in which they try to find the best mix of players against the opponent in terms of collective game statistics. Reflection of these statistics to the game by means of true performance indication and aggregated efficiency assessment of these indicators is the ultimate goal of every manager. Continuous monitoring of games in comparative manner can support the critical decision processes and help to foresee the teams' future efficiency and rank with respect to competitors. Dynamic efficiency analysis also identifies the abnormal deviations from a team's performance pattern in the long run. These irregularities can be beneficial in the monitoring of match fixing activities which gained critical attention in the last decade.

This thesis investigates how estimations of final league standings with DEA efficiency measures evolve as the season progresses using Turkish First Division Football League data for five seasons. The analysis was dynamically performed after each week using a very popular non-parametric frontier estimation technique (DEA). This methodology has been applied to football teams that played in Spor Toto Süper Lig between 2011 and 2016. Two different DEA models were experimented with. While one is a standard model the other one makes use of Analytic Hierarchy Process to include expert opinion in efficiency calculations. We have shown that the model that incorporated expert opinion provided better results than a standard model with no such knowledge.

The choice of variables is important in DEA research. We have conducted a correlation analysis to select a subset of variables from among the data available to us. Not all data was useful for the type of study we conducted. Transfer fees paid by teams for players are one of the important variables many researchers consider. However since these fees are paid at the beginning of the season and do not change during the season, they could not be used in our dynamic scheme. The number of spectators also was another piece of data we could not use because of the local bans on attending away games for the opposition teams.

Each using their own set of variables, researchers came to different conclusions regarding the appropriateness of using DEA efficiencies for predicting the final league tables. While research in Hass [10], Espitia-Escuer and Garcia-Cebrian [12] indicates that DEA efficiency is not always related to league results, other researchers such as Barros and Leach [25] found that correlations between points awarded and CCR efficiency scores are statistically supported. Rather than doing an analysis with whole season's data as in other research, we estimated final league standings dynamically after each week and looked into how these estimations change over the season. The prediction accuracy starts out low but improves as the season progresses reaching significant levels towards the end. It is expected that one would not be able to predict all league table positions correctly-although one would wish to be able to do so far gambling purposes. However, results from such analysis can still be beneficial to teams for improving their competitiveness by concentrating on their inefficiencies during the rest of the season as our research indicates. It is a known fact clubs try to improve their performance by identifying their weaknesses and injury related roster gaps by using mid-season transfer window. Such transfer decision can be supported by concentrating on the indicators causing the inefficiencies of the teams. It is also important to look into trends in the evolution of the efficiency scores in time rather than just a week's results as increasing or decreasing patterns could be important indicators for the overall success of a team. We highlighted several cases from the Turkish league where the analysis could have helped the teams.

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Appendices

Appendix A

A.1 Data

Table A.1: Sample data. Week 34 in 2011-2012.

Teams	Goal Ratio	Goal positions	Shots on target	Crosses on target	Corner kicks	Ball possession (%)
Ankaragücü	0.286	95	108	111	133	43
Antalyaspor	0.762	137	136	194	158	48
Başakşehir	0.980	186	211	177	175	42
Beşiktaş	1.316	182	182	177	188	51
Bursaspor	1.257	172	175	194	172	50
Eskişehirspor	1.024	167	175	191	155	49
Fenerbahçe	1.794	189	190	140	175	55
Galatasaray	2.875	188	218	176	187	54
Gaziantepspor	1.182	139	171	148	158	52
Gençlerbirliği	1.021	150	155	160	137	45
Karabükspor	0.772	149	155	124	139	49
Kayserispor	1.077	139	152	159	168	47
Manisaspor	0.596	135	136	150	149	47
Mersin İdmanyurdu	0.756	126	144	277	153	43
Orduspor	0.824	111	129	182	161	38
Samsunspor	0.766	131	146	170	168	42
Sivasspor	1.056	177	177	199	173	44
Trabzonspor	1.538	198	195	115	168	50

Table A.2: Sample data. Week 34 in 2012-2013.

Teams	Goal Ratio	Goal positions	Shots on target	Crosses on target	Corner kicks	Ball possession (%)
Akhisar Belediyespor	0.818	155	145	157	158	44
Antalyaspor	0.962	157	146	124	143	48
Başakşehir	0.860	133	149	135	187	47
Beşiktaş	1.286	197	196	139	194	49
Bursaspor	1.268	179	172	160	196	49
Elazığspor	0.674	114	101	138	129	48
Eskişehirspor	1.200	178	190	194	161	55
Fenerbahçe	1.436	191	188	207	227	57
Galatasaray	1.886	187	202	145	184	58
Gaziantepspor	0.840	151	153	148	149	49
Gençlerbirliği	0.979	143	154	140	146	47
Karabükspor	0.774	139	175	133	144	47
Kasımpaşa	1.297	166	154	151	153	47
Kayserispor	1.089	168	170	122	173	50
Mersin İdmanyurdu	0.585	115	117	154	136	55
Orduspor	0.686	139	139	164	161	46
Sivasspor	0.913	162	171	136	172	45
Trabzonspor	0.951	161	155	130	168	50

Table A.3: Sample data. Week 34 in 2013-2014.

Teams	Goal Ratio	Goal positions	Shots on target	Crosses on target	Corner kicks	Ball possession (%)
Akhisar Belediyespor	0.800	158	160	151	172	46
Antalyaspor	0.739	150	127	128	149	49
Beşiktaş	1.688	176	170	133	181	56
Bursaspor	0.870	190	180	173	211	47
Çaykur Rizespor	1.000	143	141	101	167	48
Elazığspor	0.613	143	146	150	167	47
Erciyespor	0.680	142	153	145	154	46
Eskişehirspor	0.943	146	159	114	182	54
Fenerbahçe	2.242	223	235	180	211	56
Galatasaray	1.758	196	200	184	179	53
Gaziantepspor	0.655	145	151	108	159	45
Gençlerbirliği	0.907	146	140	124	156	50
Karabükspor	0.971	151	167	148	174	47
Kasımpaşa	1.436	199	184	148	166	49
Kayserispor	0.526	167	157	122	175	52
Konyaspor	1.067	162	147	156	152	48
Sivasspor	1.091	169	181	128	137	53
Trabzonspor	1.293	175	191	108	168	46

Table A.4: Sample data. Week 34 in 2014-2015.

Teams	Goal Ratio	Goal positions	Shots on target	Crosses on target	Corner kicks	Ball possession (%)
Akhisar Belediyespor	0.804	129	155	111	114	48
Balıkesirspor	0.696	136	138	105	143	40
Başakşehir	1.633	165	190	127	153	47
Beşiktaş	1.719	187	189	119	172	55
Bursaspor	1.568	229	223	164	183	51
Çaykur Rizespor	0.745	167	152	132	156	46
Eskişehirspor	0.865	132	148	130	151	50
Fenerbahçe	2.069	164	181	127	184	50
Galatasaray	1.714	223	204	210	217	58
Gaziantepspor	0.646	196	202	140	190	53
Gençlerbirliği	1.070	126	136	138	128	46
Karabükspor	0.688	138	147	124	146	48
Kasımpaşa	0.778	137	155	104	170	52
Kayserispor	0.694	196	200	119	144	49
Konyaspor	0.789	139	158	109	187	47
Mersin İdmanyurdu	1.125	150	168	133	121	49
Sivasspor	0.860	182	159	168	171	52
Trabzonspor	1.208	175	186	177	166	51

Table A.5: Sample data. Week 34 in 2015-2016.

Teams	Goal Ratio	Goal positions	Shots on target	Crosses on target	Corner kicks	Ball possession (%)
Akhisar Belediyespor	1.024	132	136	77	120	47
Antalyaspor	1.000	162	162	84	164	50
Başakşehir	1.500	157	163	104	151	50
Beşiktaş	2.143	226	220	116	221	57
Bursaspor	0.855	149	148	128	151	50
Çaykur Rizespor	0.813	150	145	118	152	46
Eskişehirspor	0.619	131	144	76	146	47
Fenerbahçe	2.222	221	203	165	219	56
Galatasaray	1.408	206	207	119	170	55
Gaziantepspor	0.620	103	124	73	124	47
Gençlerbirliği	1.000	133	131	89	148	46
Kasımpaşa	1.250	176	186	117	174	50
Kayserispor	0.610	139	137	83	181	48
Konyaspor	1.333	133	131	77	135	48
Mersin İdmanyurdu	0.437	119	126	83	155	48
Osmanlıspor	1.440	167	177	80	189	46
Sivasspor	0.708	163	150	115	178	51
Trabzonspor	0.678	147	166	136	151	50

Table A.6: Correlation coefficient matrix.

	Goal Positions	Assists	Shots on Target	Passes on Target	Crosses on Target	Ball Touches	Tackles	Turnovers	Corners	Free Kicks	Ball Possession (%)
Goal Positions	1.00										
Assists	0.82	1.00									
Shots on Target	0.96	0.85	1.00								
Passes on Target	0.81	0.76	0.80	1.00							
Crosses on Target	0.68	0.48	0.63	0.57	1.00						
Ball Touches	0.84	0.78	0.82	0.99	0.56	1.00					
Tackles	0.75	0.79	0.78	0.68	0.50	0.71	1.00				
Turnovers	0.60	0.55	0.62	0.56	0.38	0.59	0.74	1.00			
Corners	0.85	0.59	0.78	0.53	0.54	0.57	0.58	0.60	1.00		
Free Kicks	0.13	-0.03	0.11	0.11	-0.25	0.13	0.16	0.50	0.41	1.00	
Ball Possession	0.87	0.71	0.83	0.92	0.68	0.93	0.63	0.62	0.70	0.18	1.00

A.2 Analytic Hierarchy Process

Table A.7: Comparison matrix for the inputs by Expert 1.

	Goal positions	Shots on target	Crosses on target	Corner kicks	Ball possession (%)
Goal positions	1	1/7	9	9	9
Shots on target	7	1	7	9	7
Crosses on target	1/9	1/7	1	1	3
Corner kicks	1/9	1/9	1	1	1/5
Ball possession	1/9	1/7	1/3	5	1

Table A.8: Comparison matrix for the inputs by Expert 2.

	Goal positions	Shots on target	Crosses on target	Corner kicks	Ball possession (%)
Goal positions	1	7	5	5	5
Shots on target	1/7	1	7	9	1/9
Crosses on target	1/5	1/7	1	7	1/9
Corner kicks	1/5	1/9	1/9	1	1/9
Ball possession	1/5	9	9	9	1

Table A.9: Comparison matrix for the inputs by Expert 3.

	Goal positions	Shots on target	Crosses on target	Corner kicks	Ball possession (%)
Goal positions	1	7	5	9	5
Shots on target	1/7	1	9	9	9
Crosses on target	1/5	1/9	1	1	1
Corner kicks	1/9	1/9	1	1	1
Ball possession	1/5	1/9	1	1	1

Table A.10: Comparison matrix for the inputs by Expert 4.

	Goal positions	Shots on target	Crosses on target	Corner kicks	Ball possession (%)
Goal positions	1	3	1	9	5
Shots on target	1/3	1	7	7	3
Crosses on target	1	1/7	1	3	7
Corner kicks	1/9	1/7	1/3	1	1/5
Ball possession	1/5	1/3	1/7	5	1

Table A.11: Comparison matrix for the inputs by Expert 5.

	Goal positions	Shots on target	Crosses on target	Corner kicks	Ball possession (%)
Goal positions	1	1/7	9	9	9
Shots on target	7	1	7	9	7
Crosses on target	1/9	1/7	1	1	3
Corner kicks	1/9	1/9	1	1	1/5
Ball possession	1/9	1/7	1/3	5	1

Table A.12: Random Index Table.

n	1	2	3	4	5	6	7	8	9	10
RI	0.00	0.00	0.58	0.90	**1.12**	1.24	1.32	1.41	1.46	1.49

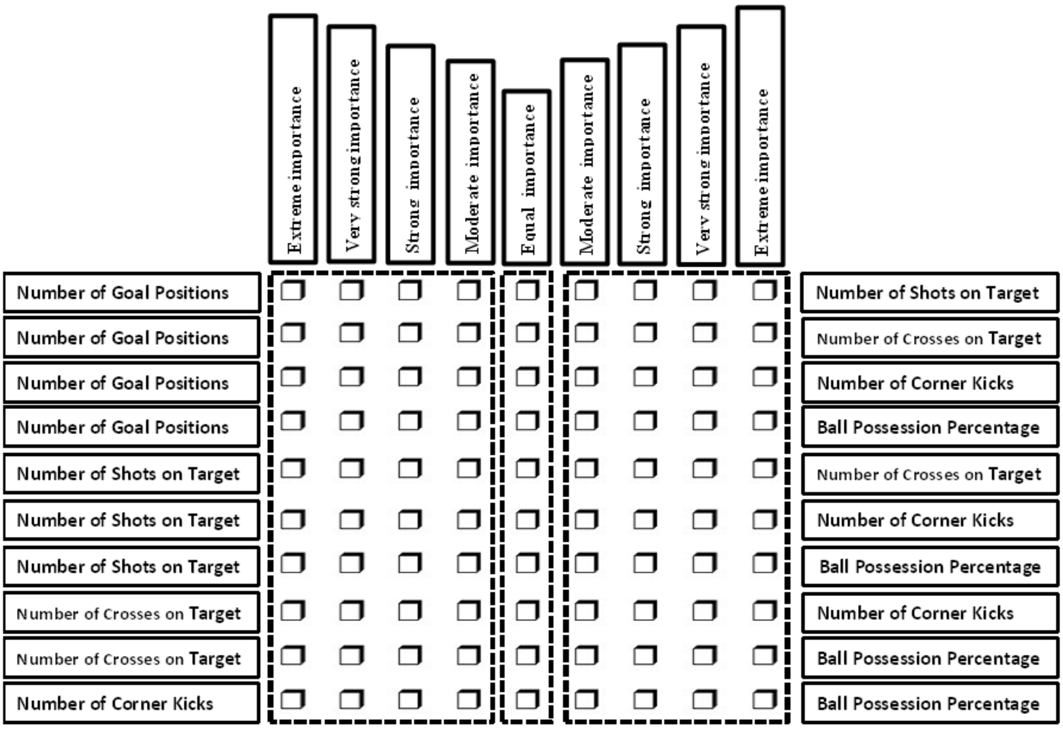

Figure A.1: AHP questionnaire.

A.3 Pearson Correlation Coefficients Results

Table A.13: Regression on rank: Final league standings vs. DEA estimations (R-square %) results.

Season	2011-2012		2012-2013		2013-2014		2014-2015		2015-2016	
Model	**CCR**	**AR**	**CCR**	**AR**	**CCR**	**AR**	**CCR**	**AR**	**CCR**	**AR**
Week 1	2.6	0.8	0.0	0.0	3.3	0.7	2.1	14.7	5.4	5.4
Week 2	0.1	1.1	11.9	7.1	29.6	37.4	14.9	17.0	1.7	10.4
Week 3	2.7	4.0	0.3	0.7	21.3	14.2	3.0	21.9	6.7	21.5
Week 4	20.9	21.7	4.3	6.2	3.6	12.8	18.5	22.0	12.0	26.4
Week 5	41.7	32.3	5.7	10.9	20.0	26.3	8.1	14.7	25.3	40.5
Week 6	39.8	40.4	0.6	0.3	9.8	18.2	14.5	26.9	52.5	56.3
Week 7	32.5	28.7	4.8	4.7	16.0	18.9	5.4	8.3	52.9	53.8
Week 8	27.1	18.0	0.9	2.6	12.7	18.5	6.9	12.8	69.3	63.6
Week 9	23.6	22.2	3.8	15.5	16.8	21.8	5.0	22.0	60.5	67.7
Week 10	20.6	20.0	16.7	19.2	27.8	35.4	14.2	36.4	54.0	59.2
Week 11	25.3	19.1	19.5	21.4	38.3	45.2	13.1	28.5	67.4	67.0
Week 12	18.0	16.0	31.4	24.6	44.0	52.0	21.3	32.3	68.7	68.3
Week 13	23.2	17.8	32.3	35.0	26.4	45.8	20.9	51.7	65.3	65.3
Week 14	35.4	28.0	20.9	25.3	37.9	36.9	26.1	46.0	68.7	66.3
Week 15	30.9	25.5	34.4	39.6	47.4	58.0	35.0	41.9	66.4	61.7
Week 16	40.5	34.0	32.1	39.6	52.0	56.3	36.9	52.0	66.1	64.0
Week 17	42.7	39.5	24.5	36.4	59.2	69.7	42.1	59.4	62.7	63.3
Week 18	57.5	52.9	27.0	39.1	61.8	71.0	48.2	59.4	66.1	68.0
Week 19	49.7	48.0	21.7	27.7	62.4	68.0	52.3	62.7	70.0	71.4
Week 20	44.9	58.5	18.5	20.3	68.7	74.5	53.0	61.5	69.4	72.1
Week 21	60.1	61.7	26.8	33.8	63.0	70.7	50.5	53.5	69.4	71.8
Week 22	50.9	56.0	30.3	42.7	64.0	73.8	48.8	54.8	72.1	72.1
Week 23	61.4	64.3	32.0	46.8	62.4	65.3	49.7	53.2	76.0	79.0
Week 24	56.9	64.0	38.1	47.7	59.6	63.7	56.5	68.0	86.1	84.2
Week 25	53.8	62.7	35.9	51.7	54.3	55.1	56.5	61.0	87.3	88.4
Week 26	62.0	65.0	33.5	48.2	56.5	58.9	59.2	68.0	85.8	88.8
Week 27	54.8	65.6	30.7	48.0	71.8	66.0	56.8	68.0	86.1	88.8
Week 28	61.0	71.8	53.7	60.7	66.4	65.1	68.0	73.8	86.4	89.9
Week 29	64.6	69.0	52.3	64.3	65.3	68.7	63.2	63.4	85.3	87.7
Week 30	61.4	69.0	60.5	65.3	66.7	67.0	68.7	73.1	71.0	83.0
Week 31	57.8	62.0	60.1	66.3	68.0	70.0	71.0	72.5	81.3	84.5
Week 32	57.5	72.8	64.0	76.8	76.4	76.8	74.7	73.2	82.4	90.7
Week 33	64.0	73.2	72.8	79.3	72.4	73.9	73.7	71.4	89.2	88.0
Week 34	67.7	72.5	74.6	81.9	69.0	73.9	68.5	70.7	90.8	89.9

Table A.14: Regression on rank: Weekly league standings vs. DEA estimations (R-square %) results.

Season	2011-2012		2012-2013		2013-2014		2014-2015		2015-2016	
Model	**CCR**	**AR**	**CCR**	**AR**	**CCR**	**AR**	**CCR**	**AR**	**CCR**	**AR**
Week 1	47.8	83.0	61.2	67.0	55.3	59.6	43.1	67.3	75.8	74.3
Week 2	70.8	89.7	74.5	79.6	72.0	84.3	18.2	45.1	56.8	65.0
Week 3	78.6	86.1	63.1	67.0	67.7	80.4	42.9	48.5	60.8	74.3
Week 4	77.9	83.4	72.7	79.3	52.9	82.0	51.6	54.4	65.2	80.6
Week 5	83.2	88.4	76.1	83.1	59.1	73.2	41.8	46.8	50.9	69.7
Week 6	94.6	95.8	72.5	69.7	56.0	77.8	22.7	41.6	67.7	67.7
Week 7	78.7	81.5	89.3	83.8	62.0	84.3	27.6	38.0	62.7	64.3
Week 8	73.4	77.7	65.3	67.7	62.8	79.1	16.7	24.0	79.5	80.1
Week 9	74.4	81.2	58.0	78.4	72.9	80.2	11.0	32.8	66.0	71.4
Week 10	72.4	76.8	85.7	88.0	87.6	82.4	14.3	34.0	76.3	74.3
Week 11	85.6	80.1	72.3	77.0	88.5	91.1	18.1	33.3	82.0	80.1
Week 12	82.1	81.3	75.3	68.3	82.4	90.3	40.3	49.1	79.6	81.1
Week 13	84.2	85.0	68.3	72.8	76.0	90.5	40.5	69.0	80.8	78.2
Week 14	59.2	64.3	67.6	75.3	87.2	86.0	49.1	68.0	79.3	80.4
Week 15	65.6	72.1	68.9	80.6	80.6	86.9	52.3	60.7	75.7	76.0
Week 16	78.6	86.8	71.0	79.1	83.9	89.2	50.9	65.3	80.4	75.6
Week 17	83.4	92.7	78.2	82.8	80.6	89.6	61.7	73.2	80.2	79.5
Week 18	81.5	85.7	77.7	77.0	86.1	92.0	58.2	68.0	82.8	82.7
Week 19	84.9	86.1	66.1	73.8	83.9	86.1	49.5	55.1	84.2	84.2
Week 20	81.5	94.3	57.7	64.0	83.5	89.6	48.3	52.0	84.2	82.0
Week 21	84.2	92.7	59.9	68.3	74.3	83.8	58.6	62.3	86.5	85.3
Week 22	66.6	79.7	62.1	75.0	79.8	88.0	56.6	56.0	72.1	72.0
Week 23	86.1	88.8	50.1	67.7	71.4	78.8	56.3	55.7	84.5	86.1
Week 24	78.6	88.4	64.0	76.8	57.7	64.0	68.0	75.7	93.1	90.0
Week 25	80.1	85.3	56.5	76.3	57.1	56.0	66.7	65.0	88.0	87.2
Week 26	86.5	89.6	63.4	79.3	69.4	70.7	71.0	76.8	89.2	84.2
Week 27	80.8	87.2	53.2	74.8	80.5	74.5	70.3	77.5	86.5	85.0
Week 28	78.2	87.6	66.7	79.7	77.1	75.1	75.1	77.3	83.1	82.7
Week 29	69.7	76.0	62.0	78.0	63.7	69.7	68.4	68.7	89.4	87.6
Week 30	64.6	75.7	65.3	75.0	72.8	71.0	72.0	74.1	76.1	78.2
Week 31	69.4	71.4	74.3	82.3	69.4	71.1	73.8	75.3	83.1	86.5
Week 32	67.3	81.5	71.4	86.1	74.0	74.6	77.5	74.6	86.0	93.4
Week 33	70.0	78.2	75.0	84.2	72.8	73.5	74.0	74.3	88.0	88.8
Week 34	67.7	72.5	74.6	81.9	69.0	73.9	68.4	70.7	90.8	89.9