A defensive basketball efficiency score using data envelopment analysis

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ABSTRACT

A multiple criteria model of a college basketball team's defensive efficiency is developed using modern digital video data collection capabilities and data envelopment analysis (DEA) methods. One goal of sports analytic research is to build a data-driven baseline for decision-making for college athletic directors, scouts, players, and coaches. The data analysis supports the decision of the athletic director to fire the coach. This article makes other contributions to the sports analytics and performance measurement literature by evaluating continuous improvement, and defining a new defensive metric--contested shots.

Key words: performance measurement, sports analytics, service operations management, data envelopment analysis, continuous improvement, benchmarking

INTRODUCTION

The coach of any sports team must review the results of each game confronted with synthesizing multiple criteria into an evaluation of the player or team, that is, the asset(s). A player is an individual asset whereas a team is a set of pooled assets. The human mind must integrate as many as a dozen basketball performance metrics to make decisions. At the amateur college level, these decisions include who starts and the rank order of substitutes, best and worst performance player and team benchmarks, practice drills to improve player and team performance, player acquisition, and team decisions and strategy (i.e., the game plan and coaching). In addition, media sports pundits, professional agents, and sports fans engage in similar mental analyses. As the number of performance metrics increase the variance of decisions and opinions also increase to the point where the solution space represents thousands to millions of combinations. To support stakeholder decision-making, an analytically based decision support system that models multiple criteria is needed. Such a system is not a replacement for coach and player judgment but it does provide an objective baseline for human decision-making.

Although our focus is U.S. college (amateur) athletics, college leagues and teams sign big television contracts. The NCAA, for example, signed a $10.8 billion dollar 14-year contract with CBS and Turner Broadcasting to televise the men's' NCAA basketball tournament. The South Eastern Conference (SEC) reported signing a contract with ESPN for $2.5 billion for broadcast rights to SEC football games from 2009 to 2025. CBS and the ESPN family of networks, which includes ABC, ESPN, ESPN2, and ESPNU provide SEC coverage. The SEC in the last six years has won 84 percent of its regular-season non-conference football games, and more than two-thirds of its bowl matchups (Wieberg, 2012).

The main story line of the popular movie *Moneyball* reinforced the benefits of sports analytics. In the movie, professional baseball managers and coaches through mathematical analysis could find high performance players at low prices before competitors could identify and sign them. On-base percentage in baseball, for example, is a better measure of a hitter's performance, than the century old metric of average batting average. Likewise, the growth in the MIT Sloan Sports Analytics Conference founded in 2006 establishes the increasing role of business analytics in leisure and sports industries.

The goal of defense in basketball is to frustrate and antagonize the offense in a way that encourages a change of possession and the lowest number of total opponent points. Defensive prowess is an undervalued basketball capability that tends to be highlighted mainly during tournament play when "defense wins championships." As Coach John Calipari, coach of the 2012 National Basketball Champion University of Kentucky said after their victory over Kansas, "I wanted them (the players) to show today that we were not just a talented team, we were a defensive team, and we were a team that shared the ball. I wanted everybody to see it. We were the best team this season. The most efficient team." (*The Cats Pause*, 2012, p. 13)

Amateur college basketball defensive players and teams are evaluated on traditional basketball metrics such as blocked shots, defensive rebounds, steals, forced turnovers, fouls, and the opponent's total points and field goal shooting percentage. In this article we introduce one new defensive basketball metric---contested shots. A contested pass was introduced in a previous article (CCC, 2011). Unlike professional basketball, the price (and value) of a player in U.S. college basketball is not available or considered here. Player and team box scores and statistics, shot and rebound charts, play-by-play time series data, and video analysis are traditional ways to summarize game performance metrics.

Stakeholders include coaches, owners, athletic directors, managers, scouts, agents, players, and fans. They have the ability to influence the processes inherent in and around a basketball game. Basketball processes are the controllable behaviors that players and teams practice and choose to execute in a game. They form the identity of a team through offensive plays, defensive schemes, and individual skills that impact winning or losing a game. The game of basketball is similar to business processes in terms of allocating resources (assets) effectively and achieving desired outcomes.

Business organizations have similar motivations and design controllable goods-producing or service-providing processes to maximize revenue and customer service while minimizing costs (DDD, 2012). If the processes are inefficient resources are wasted, mistakes are made, and internal and external improvement opportunities are lost. Methods to price and manage assets are well known in corporations such as revenue management algorithms (AAA, BBB, 2003, 2005), stock pricing and company valuation models (Treynor, 1965; Treynor and Mazuy, 1966), and supply chain and enterprise resource planning (GGG, 2000; HHH, 2000) systems.

We view the emerging field of sports analytics as the convergence of information technology, business analytic, and operations management methods and capabilities. One long-term goal of sports analytics research is to build an analytically based system to provide an objective baseline for stakeholder decision-making. Our immediate goal is to use data envelopment analysis (DEA) methods to help answer the following research questions regarding one United States college basketball team's defensive efficiency.

- What are our team's best performing (best practice) defensive halves of basketball?
- What can we learn from these best practice performance data?
- What are our team's worst performing defensive halves of basketball?
- What defensive team performance targets should we try to achieve?
- Is there evidence of continuous improvement?

We attempt to answer these questions using up to six different input and output criteria.

DATA ENVELOPMENT ANALYSIS

Data envelopment analysis (DEA) can be used to assess the comparative multi-factor efficiency of players and teams, and thereby, provide the first step toward improving the efficiency of stakeholder decisions. Charnes et al. (1978) are credited with pioneering the concept of DEA. Foundation books and articles that encompass DEA methods and assumptions include Charnes et al. (1994), Cooper et al. (2000), Petroni and Bevilacqua (2002), and Thanassoulis, E. (2001). Seiford (1996) presented a comprehensive literature review of theoretical and application-oriented DEA articles and traced the evolution of the field. Popular DEA software programs include BANXIA Frontier Analyst (2010) and PIM DEA Soft-V3 (2010).

The basic idea behind DEA is the "relative" measurement of performance, which is generally defined as the effectiveness of a set of homogenous *decision-making units (DMUs)* in realizing output(s) created through the utilization of input(s). DEA requires a small number of observations for effective use compared to parametric statistical methods. DEA is also a deterministic numerical method that makes minimal assumptions (Charnes et al., 1978, 1994;

Cooper, et al. 2000; Emnouznejad and Witte, 2010; Thanassoulis, 2001).

A DMU can be a sports player, team, manager, athletic director, coach, or a game or part of a game. DEA allows one to identify the best practice and 100% efficient DMU(s) and compare these to the inefficient DMUs. As a result, insights are gained as to how to improve inefficient DMUs. The DMU, for example, may be a sports player or team (Barros and Leach, 2006), a hospital or health clinic (Al-Shammari, 1999), a branch bank (Soteriou and Zenios, 1999; Manandhar and Tang, 2002), individual physician performance (EEE, FFF, 2006), and an electrical utility (Blose and Tankersley, 2004).

Norman and Stoker (1991, p. 15) and Charnes and Cooper (1978, 1994) define DEA efficiency as follows: "100% relative efficiency is attained by any (unit) only when comparisons with other relevant (units) do not provide evidence of inefficiency in the use of any input or output." They also state that 100% efficiency is attained for a unit only when: (a) None of its outputs can be increased without either (i) increasing one or more of its inputs, or (ii) decreasing some of its other outputs; (b) None of its inputs can be decreased without either (i) decreasing some of its outputs, or (ii) increasing some of its other inputs."

DEA works by identifying and plotting an implicit piece-wise-linear programming based "efficiency frontier" based on the input-output levels in the data. The frontier is determined by the extreme (boundary) DMUs (observations), and therefore, is sometimes faulted for being too sensitive to extreme observations that might simply be outliners or inconsistencies in the data set. An advantage of DEA is that it is somewhat insensitive to sample size (to be explained in detail later), and therefore, is amendable to small sample sizes.

Banker, et al. (1989) suggests an approximate rule of thumb regarding an adequate DEA sample size. That is, if p is the number of inputs and q is the number of outputs used in the DEA analysis, then the sample size n should satisfy $n \geq max$ [p x q; 3(p + q)]. For the results shown here we have $n \geq max$ [1 x 2; 3(1 + 2)] = max [2, 9] = 9 DMUs while we have 20. Fitzsimmons (2011, p. 205) cites a second general rule for an adequate DEA sample size where the number of service units (DMUs) in the analysis should meet the following requirement where p and q are as previously defined. In our situation, K = 20 and K ≥ 2(p + q) so 20 ≥ 2(1 + 2) or 20 ≥ 6. The latter rule is not as restrictive as the former rule. Therefore, we have an adequate sample size for the DEA results shown in Tables 1 and Figure 1.

Applying these same DEA sample size rules we find that the maximum number of inputs plus outputs we can model is about six. That is, $n \geq max$ [p x q; 3(p + q)], so 20 ≥ max [5 x 1; 3(5 + 1)] = max (5, 18) = 18 and 20 ≥ 18. Hence, a total of six input plus output variables is our limit.

SPORTS LITERATURE

One excellent article on basketball sports analytics is by Kubatko, et. al (2007) that depicts clever ways to define basketball performance. Possessions, for example, are defined as "when one team gains control or possession of the basketball and ends when that team gives up control of the basketball." Using a two-sample t-test of means (Minitab, 2011) on our data set, there was no statistical difference (df = 37, p = .999) in the 20 halves of basketball for the number of possessions of the two opponents. Therefore, there is no need to correct our data set per possession. Martinez and Martinez (2011) provide another good article on basketball player metrics including posing seven research questions.

Another significant development and capability in sports analytics is motion-capture technology. Sportvision's Field/x system, for example, tracks every player on the baseball field and logs their movements 20 times per second (Boudway, 2011). Each outfielder, for example, is evaluated on number of steps to catch the ball, ball hang time, quickness of responding to a hit, and distance to catch the ball. Basketball and soccer also use this technology.

Maymin and Maymin (2011) take a different approach to sports analytics research that helps players and coaches understand how to improve free throw shooting. Their research can be viewed as an applied paper on physics. They use three-dimensional optical tracking data at 25-frames-per-second to analyze 2,400 free throw shots by players during the 2010-2011 NBA season. They use criteria like backspin, angle, velocity, and initial launch height to define the perfect free throw and then examine 158 NBA games during the regular season. They conclude that why players miss free throws is consistent by player but differs widely from player to player.

Structural equation modeling (LISREL, 2011) has also been used to create NBA offensive and defensive (quality) latent variables using four factors—effective field goal percentage, free throw rate, turnovers per possession, and offensive rebounding percentage (Baghal, 2012). Baghal uses the formulas commonly accepted by Kubatko, et al. (2007) to test a casual model where offensive and defensive qualities are hypothesized to cause (influence) the game winning percentage. Their structural equation model (SEM) did not meet some standard statistical model tests such as the chi-square test statistic but they do demonstrate the use of SEM in sports analytics. They also incorporated player salaries into a second SEM. One interesting finding is that the relationship between NBA salary and defensive quality is not statistically significant. Their research suggests a strong statistical relationship between salary and offensive quality but the impact on winning percentage remained about the same with and without salary included in the structural model.

Stekler and Klein (2012) use probit models to predict the winners of the first four rounds of the NCAA basketball tournament (i.e., March Madness). They use the difference in regional rankings (i.e., seeds) to predict winners and losers. Their results work well for the first three rounds of tournament but in the regional championship round (i.e., final eight teams) you would do just as well predicting the winners by flipping a coin. West (2006) uses an ordinal logistic regression and expectation (OLRE) model to predict the expected number of wins (success) for teams selected by the NCAA basketball tournament selection committee. The model uses wins as the dependent variable and four independent variables (i.e., strength of schedule metric by Jeff Sagarin, the number of wins against top thirty teams, the team's winning percentage, and a team's point differential for the season). The OLRE methods provide slightly better predictions based on lower sum of squared errors than a competing Bradley-Terry model. West also critiques the Ratings Percentage Index (RPI) used by the NCAA selection committee and Jeff Sagarin's computer ratings.

As mentioned previously, Barros and Leach (2006) use DEA to evaluate English Premier League football (soccer) clubs from 1998/99 to 2002/03 combining sport and financial variables. The paper evaluates how close the clubs are relative to the best practice frontier. Ruiz, et al. (2011) also use DEA to evaluate the performance of professional tennis players. They use data from the Association of Tennis Professionals (ATP) that focuses solely on nine outputs like percentage of second serve points won and percentage of break points won. Their single input is a constant value of one that indicates each player is performing as good as they can and no other resources (inputs) are used (consumed). Comparing their DEA-based efficiency player scores to ATP point rankings results in a Spearman rank correlation of .933, and therefore, the two professional tennis player rankings are similar with a few interesting differences. Their DEA analysis provides more insight than the ATP rankings into the weaknesses and strengths of each professional tennis player.

One sports analytics research challenge is that once terabytes of data are collected, how do you analyze it? A second challenge is to recognize the diverse data analysis methods being applied to evaluate performance in a sports event. A third challenge is the human resistance to change where recruiting and coaching were historically considered an art and not based on data-driven business analytics. Sports stakeholders have little expertise in analytical methods and models, and therefore, resist change. We must remind sports stakeholders that we do not intend to replace people with software but to build a decision support system based on business analytics.

DATA COLLECTION METHODS AND SOFTWARE

After defensive performance criteria were defined including new metrics like contested passes (CCC, 2011) and contested shots, we used digital video recording and specialized software called *Gamebreaker* (2011) to gathered performance data on a college basketball team from the 2010-2011 season. *GameBreaker* records this video data as the game progresses on a continuous time frame. We set up the software to collect data on over 35 game metrics by player, team, and type of basketball event. A total of 20 halves of college basketball were meticulously coded creating a small but comprehensive data set.

RESULTS

A DMU is defined as one half of a basketball game. The data set and DEA results for two defensive and one opponent's (offensive) criteria (called Model A) are shown in Table 1 (Appendix). The two defensive outputs are defensive rebounds (DR) and contested shots (CS), and the one input metric is total opponent points (TOP). The Appendix also provides a definition of a contested shot along with coding rules and behaviors. These rules and behaviors reflect "standards of performance" much like specifications for a manufactured part (product quality) or average waiting time for service (service quality). In this situation, please note that the output of a basketball defense is DR and CS. These results are based on the assumption of constant returns to scale (Thanassoulis, 2001, pp. 22-31) and the data are from a single basketball season. Each half of basketball is coded in Table 1 by opponent letter (A, B, E, J, L, M, or U), the next number is the first or second game, and the last number is the first or second half.

DEA Model A

Based on three criteria, DR, CS and TOP used in DEA Model A; the two halves, J21 and L21, are 100 percent efficient and are graph in Figure 1 (Appendix). The DEA efficiency scores range from 100% to 39.94 percent with the L22 half being this team's worst defensive half. Notice in Table 1 that L22 produced 9 defensive rebounds, 12 contested shots, and allowed 52 total opponent points. That combination of inputs and outputs results in the lowest efficiency score for the 20 DMUs. The average defensive team efficiency is 74.99 percent.

Given the obvious clustering of team defensive performance shown in Table 1 and Figure 1 (Appendix), three performance clusters are defined as follows. Cluster A includes eight "best practice" DMUs with efficiency scores ranging from 91.07 to 100 percent with an average score of 97.12 percent. Cluster B includes six DMUs with efficiency scores ranging from 63.64 to

82.50 percent with an average score of 73.95 percent. Cluster C represents six low performing DMUs with efficiency scores ranging from 39.94 to 51.14 percent with an average score of 46.52 percent.

A full set of improvement initiatives for each half of non-efficient defensive basketball is available from the DEA results. DMU B21, for example, is 91.07 percent efficient and can attain 100 percent efficiency by increasing its defensive rebounds from 10 to 11, and reducing the total opponent points scored from 28 to 25 points. Likewise, B11 is 76.92 percent efficient and must increase its contested shots from 15 to 19 and reduce total opponent points from 42 to 32 to become 100 percent efficient. These results indicate that team defensive performances were diverse and there is much opportunity for improvement.

Figure 1 based on the performance data in Table 1 defines the DEA efficiency frontier where J21 and L21 were our "best practice" defensive halves. Cluster A includes eight DMUs with an average efficiency score of 97.12 percent while Cluster B includes six moderate performing DMUs with an average efficiency score of 73.95 percent. In Cluster A, DMUs A11, J11, and M12 overlap so in Figure 1 you see only seven of the eight DMUs clearly.

Cluster C includes six poor performing and non-efficient DMUs with an average efficiency score of 46.52 percent. Non-efficient halves aspire to improve by reaching the efficiency frontier. Notice that all six Cluster C DMUs are in the second half of the basketball game. Given this college team is in the lower quartile of NCAA Division I basketball programs based on computer power ratings, one explanation of Cluster C results is that the team does not have adequate player talent and/or depth to continue to play high-energy defense during the second half. This team is losing games in the second half, in part, due to defensive inefficiencies.

DEA Models B and C

Alternative DEA models, Models B and C, using more input and output criteria are shown in Table 2 (Appendix) but cannot be graphed. DEA Model B continues to use TOP as the input variable with forced turnovers (FTO), defensive rebounds (DR), total fouls (TF), contested shots (CS) and defensive steals (DS), as outputs. DEA Model C, adhering to our constraint of no more than six total input and output variables, uses two inputs and four outputs of the defensive team. The two inputs are total opponent points (TOP) and field goal percentage (FG%) with the defensive outputs being FTO, DR, TF, and CS. Model C results in eight DMUs being 97.75 to 100 percent efficient.

A Krushal-Wallis non-parametric test of the equality of sample medians for Models A, B and C reveals a test static H = 1.6, df = 2,and P = 0.451. The sample median efficiency scores (and Z-values) for Models A, B, and C are 0.7846 (-1.26), 0.8009 (0.60), and 0.8098 (0.66), respectively. These statistics suggest the null hypothesis of equal medians cannot be rejected. Therefore, the three DEA models in Table 2 provide statistically equivalent median efficiency scores although individual DMU results can be different such as B12 for Model A is 47.87% efficient versus Model C 67.34% efficient.

The more comprehensive DEA Models B and C did generate higher efficiency scores than Model A as shown in Table 2 but overall there was marginal value in going from Model A to Model B or C. Moreover, the correlation between FG% and TOP was high at 0.719 so adding similar input criteria did not have a big impact.

We also examined the DEA results for evidence of continuous improvement by evaluating DEA efficiencies as a function of time (i.e., game schedule). We had hoped to demonstrate the methods available to objectively evaluate continuous improvement. However, the correlation matrix in Table 3 (Appendix) provides evidence that no continuous improvement existed.

For Model A, if one takes the differences between first and second half DEA efficiencies we find in only two games out of ten did DEA efficiency scores increase in the second half while for the other eight games they decreased. For example, for Cluster C the average DEA efficiency for the first half is 88.47 percent and for the second half 46.52 percent. As previously mentioned, hypotheses as to why this huge decrease in defensive team efficiency from the first to second half focuses on this team not having adequate depth of players, lack of player talent, and poor coaching adjustments at half time.

CONCLUSION & DISCUSSION

DEA was used to compute team defensive efficiency scores using up to six input/output criteria for 20 halves of college basketball. We identified the best practice defensive halves, Cluster A, which coaches can show players to improve performance and set achievable performance targets. The most inefficient halves of defensive basketball, Cluster C, were found to show players how not to play defense. Results document a huge decrease in defensive efficiency from the first to second halves. In addition, we found our simple DEA model; Model A, provided roughly equivalent DEA efficiencies compared to using our six variable Model's B and C. All results use a new defensive metric—contested shots. The Appendix defines contested shots, and standard coding rules and defensive behaviors. Finally, there was no evidence of continuous improvement. These data-driven results support the athletic director's decision at the end of the season to fire the coach and his entire staff. Performance analysis such as shown here can be used to support management decision making by university presidents, athletic directors, and other sports stakeholders.

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APPENDIX

DEFINITION AND STANDARD RULES OF PLAYER BEHAVIOR FOR A ONTESTED SHOT

Traditional defensive criteria are not defined in this appendix to save space and include defensive rebounds, fouls, forced turnovers, blocked shots, and steals. These definitions and others can be found on the NCAA's website by downloading the free 2010 & 2011 NCAA Men's and Women's Basketball Rules. For more information visit http://www.ncaapublications.com/p-3941-2009-2011-mens-womens-basketball-rules-2-year-publicaton.aspx

CONTESTED SHOTS

A shot is contested when a defender is close enough (i.e., less than or equal to one foot) to the offensive player to affect his shot and makes a credible effort to do so by jumping and extending a hand towards the path of the ball or in front of the eyes of the offensive player. In addition, a contested shot is evidenced when a defensive player exhibits the behavior stated above and when an offensive player's performance has any of the following characteristics.

1) The player is forced to pump the ball while in his shooting motion and alters his shot.
2) The player shoots a ball with an unusually low or high trajectory (48 degrees is the average from the college three point line. Shots below 40 or above 60 degrees from that distance qualify to fit this criterion).
3) A player is visibly rushed and/or the basketball does not hit the rim.
4) A player abandons his shot attempt and is instead forced to pass or hold the ball or call time out.
5) A player abandons his shot attempt in favor of a turnover.

Table 1. Basketball game DEA efficiencies for Model A with two defensive outputs (DR and CS) and one offensive input (TOP)

DMU Half	CS	DR	TOP	CS/TOP	DR/TOP	DEA Defensive Efficiency
Cluster A						
J21	18	13	30	0.600	0.433	100.00%
L21	24	15	36	0.667	0.417	100.00%
J22	27	14	41	0.659	0.341	98.78%
J11	25	13	38	0.658	0.342	98.68%
E11	13	11	26	0.500	0.423	97.63%
M12	20	14	34	0.588	0.412	95.80%
A11	22	15	37	0.595	0.405	94.98%
B21	17	10	28	0.607	0.357	91.07%
Cluster B						
M11	22	9	40	0.550	0.225	82.50%
E12	16	10	30	0.533	0.333	80.00%
B11	15	14	42	0.357	0.333	76.92%
L12	17	13	42	0.405	0.310	71.43%
U11	16	12	40	0.400	0.300	69.23%
L11	14	8	33	0.424	0.242	63.64%
Cluster C						
J12	15	8	44	0.341	0.182	51.14%
U12	15	6	44	0.341	0.136	51.14%
A12	17	8	53	0.321	0.151	48.11%
B12	15	8	47	0.319	0.170	47.87%
B22	15	9	55	0.273	0.164	40.91%
L22	12	9	52	0.231	0.173	39.94%
Max	27	15	55	0.667	0.433	1.000
Min	12	6	26	0.231	0.136	0.399
Ave	17.8	11.0	39.6	0.468	0.293	0.750
Std Dev	4.2	2.8	8.2	0.142	0.103	0.220

Table 2. DEA defensive basketball efficiency scores for multiple criteria models

DMU Half	DEA Model A	DEA Model B	DEA Model C
Inputs	TOP	TOP	FG%, TOP
Outputs	DR, CS	FTO, DR, TF, CS, DS	FTO, DR, TF, CS
Best practice DMUs			
J21	**100.00%**	**100.00%**	**100.00%**
L21	**100.00%**	**100.00%**	**100.00%**
J22	98.78%	**100.00%**	99.68%
J11	98.68%	**100.00%**	**100.00%**
E11	97.63%	**100.00%**	**100.00%**
M12	95.80%	**100.00%**	**100.00%**
A11	94.98%	99.52%	99.52%
B21	91.07%	97.81%	97.75%
Moderate Performing DMUs			
M11	82.50%	83.26%	83.26%
E12	80.00%	97.57%	94.78%
B11	76.92%	76.92%	77.54%
L12	71.43%	75.20%	74.62%
U11	69.23%	70.65%	70.81%
L11	63.64%	73.96%	73.11%
Low Performing DMUs			
J12	51.14%	62.53%	59.73%
U12	51.14%	68.94%	78.70%
A12	48.11%	57.90%	52.40%
B12	47.87%	54.71%	67.34%
B22	40.91%	44.94%	44.82%
L22	39.94%	41.07%	41.95%
Max	1.000	1.000	1.000
Min	0.399	0.411	0.420
Ave	0.750	0.802	0.808
Std Dev	0.220	0.204	0.199

Table 3. DEA model defensive basketball efficiency and time correlations

DEA Efficiency	Time	Model A	Model B
Model A	-.069*		
Model B	-.074*	.969+	
Model C	-.022*	.946+	.981+

+significant at 1% (n =20)
* significant at greater than 10% (n =20)

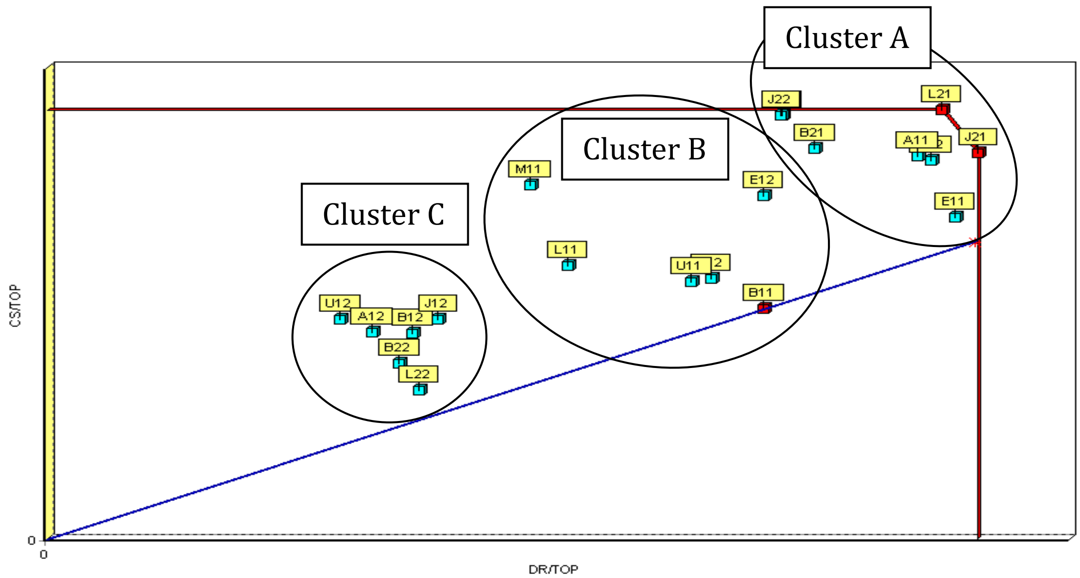

Figure 1. DEA Model A efficiency frontier graph for input minimization with two defensive outputs (contested shots and defensive rebounds) and one opponent's offensive input (total opponent points)