A Fuzzy Expert System to Estimate Basketball Player's Performance

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Introduction

This exercise draws inspiration from the field of sports analytics, particularly focusing on basketball, a sport that extensively utilizes statistical and data analysis methods. The objective is to design a fuzzy expert system capable of predicting a basketball player's winning percentage based on a set of indicators. The exercise involves constructing a simplified system with a single block of rules, acknowledging that a real-world implementation would demand a more intricate structure with additional inputs.

The task requires selecting four input variables from the paper provided, each utilizing distinct scales and units such as percentage, ratio, or measurement. Additionally, a fifth variable, "Years of experience," is introduced, influencing the way other variables are interconnected. This is crucial because player evaluation should consider the impact of experience, recognizing that a player with two years of experience cannot be assessed in the same manner as one with 15 years of experience.

Definition of Linguistic Variables

The first step in the design of an expert system is to select the variables that will be used as input and output and define their membership functions.

In the case of the output variable, the one that is going to be used is the probability of winning of the team the player belongs to.

The choice of inputs features is a key step in order to build an effective expert system. Different techniques can be used to choose those which are important and strongly related with the output. Our selection is strongly inspired in results from D'Urso et al. [1] in which, among a broad set of variables such as *Age, Assist percentage, Minutes Played, Turnover Ratio,* ... they choose the following 4 features and the last one is introduced by us:

- Possession (PACE): Number of possessions in the match.
- Minutes (MIN): Minutes played in the match.
- Offensive Rating (OFFRTG): Number of points per 100 possessions that the team scores while that individual player is on the court.
- Defensive Rating (DEFRTG): Number of points per 100 possessions that the team allows while that individual player is on the court.
- Years of Experience (YOE): Years of experience of the player as a professional.

For this selection, they design a Non Parametric Bayesian Network and study the impact of modifying independently each of the features in the variation of the probability of winning.

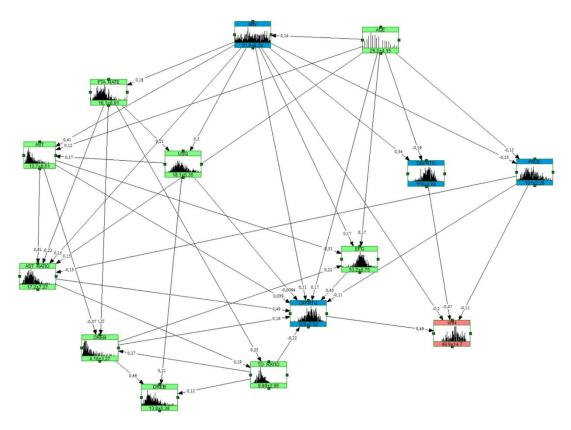


Figure 1. The estimated averaged BN under the assumption of Gaussian Copula, using the Uninet software representation with nodes replaced by monitors showing the empirical distributions. (Source: [1])

A summary of their results is:

- OFFRTG of 10% higher than the mean, thus setting the value of the OFFRTG node at 121, the mean value of the WIN node goes from 49.5 to 69.2%.
- Decrease the mean value of the DEFRTG node by 10%, fixing the value of the node at 99, the mean value of the WIN node rises to 61.7%
- Being equal the values of OFFRTG and DEFRTG, decreasing value of PACE a 5% it
 increases the mean value of the winning percentage from 50.8 to 52.7 while if it grows
 up the same amount, the mean value of the winning percentage decreases to 48.6.
- Finally, increasing the age from 26 (median) to 35, the mean value of the winning percentage goes from 53.7 to 59.4

This information can be useful to design the rules.

From Figure 1, information about the distribution of all the features can be read. Using this information, the membership function can be designed with more accurate criterion.

MIN Variable

It follows a uniform distribution from 0 to 48 (duration of a match). In terms of membership function, this means that the area of each polygon representing the terms should be equal to 16. Three terms have been defined: Low (between 0 and 17 minutes), Medium (between 17 and 33) and High (greater than 31).

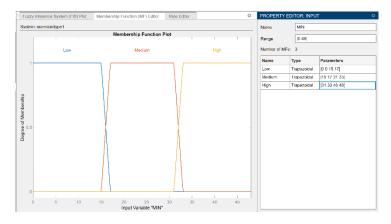


Figure 2: MIN Terms design

OFFRTG Variable

This variable can be considered to follow a gaussian distribution with a mean value of 109 and standard deviation of 5.52. This means approximately the 68% of the values will be between 103.5 and 114.5 (+- 1 std) and 99.7% between 92 and 125 (+- 3 std). In addition to this, we know that WIN is especially sensitive to this feature, so 5 terms will be included, and triangular functions are chosen in order to have a fine-grained measure and transitions.

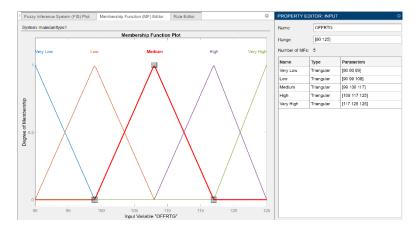


Figure 3: OFFRTG Terms design

DEFRTG Variable

Given that this measure should be the complementary of OFFRTG and the similarity among the distributions, the same terms with the same membership function is used. It can be considered High from 106 on given its average and standard deviation.

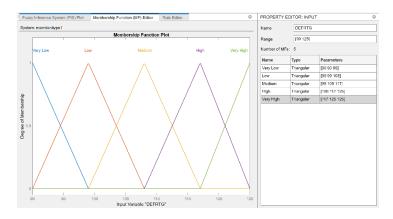


Figure 4: DEFRTG Terms design

PACE Variable

This variable behaves as a skewed gaussian. It can be considered that its range of values is the same as the ones for OFFRTG and DEFRTG. However, as the system is not very sensitive to this value, we can discard the option of having a Medium state. The skewness is represented as an asymmetry in the definition of the membership function.

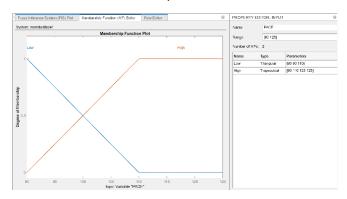


Figure 5: PACE Terms design

YOE Variable

It is a realistic approach thinking that NBA players are stars, and, as that, they started their professional careers when they were 18 years old (minimum age in AGE variable in Figure 1). This is why it can be considered that the distribution of YOE is the same as AGE but subtracting 18 to it. If it's considered that AGE follows a normal distribution, then, due to the properties of gaussian distribution, its average should be 26 - 18 years so 8 years. The standard distribution isn't affected by translation because it is a measure of how scattered data is.

As a summary, we can consider three levels of experience: Beginner, Experienced and Veteran.

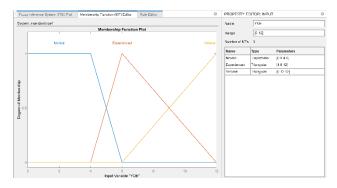


Figure 6: YOE Terms design

WIN Variable

Finally, membership function for output variable is defined. It can be considered to follow a Bernoulli distribution of parameter p equal to 0.5 (probability of win). As ties aren't very common in basketball matches, we decide to include it in "not winning" term.

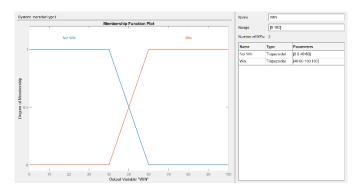


Figure 7: WIN Terms design

Rules Definition

For the definition of the rules, the 5 test cases from [1] have been implemented in addition to some extra rules added in sake of completeness. For the weight for each of rules, the result of these test cases has been used as inspiration. For example: "In the fourth scenario we investigate the role of the PACE variable. Being equal the values of OFFRTG and DEFRTG (see Fig. 6a), decreasing its value to 98 increases the mean value of the winning percentage from 50.8 to 52.7" was translated into "MIN==Medium & OFFRTG==Medium & DEFRTG==Medium & PACE==Low & YOE==Experienced => WIN=Win (0.527)"

• Rule 1:

- Conditions: MIN==Medium & OFFRTG==Very High & YOE==Experienced
- o Result: WIN=Win (0.692)
- Explanation: If a player has a medium playing time, a very high offensive rating, and is experienced, the probability of winning is 69.2%.

• Rule 2:

Conditions: MIN==Medium & OFFRTG==Medium & DEFRTG==Medium & PACE==Medium & YOE==Experienced

- o Result: WIN=Win (0.495)
- Explanation: If a player has medium playing time, a medium offensive rating, medium defensive rating, medium pace, and is experienced, the probability of winning is 49.5%.

• Rule 3:

- Conditions: MIN==Medium & OFFRTG==Medium & DEFRTG==Very Low & PACE==Medium & YOE==Experienced
- o Result: WIN=Win (0.617)
- Explanation: If a player has medium playing time, a medium offensive rating, very low defensive rating, medium pace, and is experienced, the probability of winning is 61.7%.

• Rule 4:

- Conditions: MIN==Medium & OFFRTG==Medium & DEFRTG==Low & PACE==Medium & YOE==Experienced
- o Result: WIN=Win (0.617)
- Explanation: If a player has medium playing time, a medium offensive rating, low defensive rating, medium pace, and is experienced, the probability of winning is 61.7%.

• Rule 5:

- Conditions: MIN==Medium & OFFRTG==High & DEFRTG==High & PACE==Medium & YOE==Experienced
- o Result: WIN=Win (0.57)
- Explanation: If a player has medium playing time, a high offensive rating, high defensive rating, medium pace, and is experienced, the probability of winning is 57.0%.

• Rule 6:

- Conditions: MIN==Medium & OFFRTG==High & DEFRTG==Low & PACE==Medium & YOE==Experienced
- o Result: WIN=Win (0.75)
- Explanation: If a player has medium playing time, a high offensive rating, low defensive rating, medium pace, and is experienced, the probability of winning is 75.0%.

• Rule 7:

- Conditions: MIN==Medium & OFFRTG==Medium & DEFRTG==Medium & PACE==Medium & YOE==Veteran
- o Result: WIN=Win (0.594)
- Explanation: If a player has medium playing time, a medium offensive rating, medium defensive rating, medium pace, and is a veteran, the probability of winning is 59.4%.

• Rule 8:

- Conditions: MIN==Medium & OFFRTG==Medium & DEFRTG==Medium & PACE==Low & YOE==Experienced
- Result: WIN=Win (0.527)
- Explanation: If a player has medium playing time, a medium offensive rating, medium defensive rating, low pace, and is experienced, the probability of winning is 52.7%.

• Rule 9:

- Conditions: MIN==Medium & OFFRTG==Very Low & DEFRTG==Very High & PACE==Medium & YOE==Experienced
- o Result: WIN=Win (0.62)
- Explanation: If a player has medium playing time, a very low offensive rating, very high defensive rating, medium pace, and is experienced, the probability of winning is 62.0%.

• Rule 10:

- Conditions: MIN==Medium & OFFRTG==Low & DEFRTG==High & PACE==Medium & YOE==Experienced
- o Result: WIN=Not Win (0.56)
- Explanation: If a player has medium playing time, a low offensive rating, high defensive rating, medium pace, and is experienced, the probability of losing is 56.0%.

• Rule 11:

- Conditions: MIN==High & OFFRTG==Medium & DEFRTG==Medium & PACE==Low & YOE==Veteran
- o Result: WIN=Win (0.56)
- Explanation: If a player has high playing time, a medium offensive rating, medium defensive rating, low pace, and is a veteran, the probability of winning is 56.0%.

Rule 12:

- Conditions: MIN==Medium & OFFRTG==Very High & YOE==Experienced
- o Result: WIN=Win (0.6)
- Explanation: If a player has medium playing time, a very high offensive rating, and is experienced, the probability of losing is 60%%.

• Rule 13:

- Conditions: MIN==Medium & OFFRTG==Medium & DEFRTG==Medium & PACE==Medium & YOE==Experienced
- o Result: WIN=Not Win (0.505)
- Explanation: If a player has medium playing time, a medium offensive rating, medium defensive rating, medium pace, and is experienced, the probability of losing is 50.5%.

• Rule 14:

- Conditions: MIN==Medium & OFFRTG==Medium & DEFRTG==Very Low & PACE==Medium & YOE==Experienced
- o Result: WIN=Not Win (0.383)
- Explanation: If a player has medium playing time, a medium offensive rating, very low defensive rating, medium pace, and is experienced, the probability of losing is 38.3%.

• Rule 15:

- Conditions: MIN==Medium & OFFRTG==Medium & DEFRTG==Low & PACE==Medium & YOE==Experienced
- o Result: WIN=Not Win (0.383)
- Explanation: If a player has medium playing time, a medium offensive rating, low defensive rating, medium pace, and is experienced, the probability of losing is 38.3%.

• Rule 16:

- Conditions: MIN==Medium & OFFRTG==High & DEFRTG==High & PACE==Medium & YOE==Experienced
- o Result: WIN=Not Win (0.43)
- Explanation: If a player has medium playing time, a high offensive rating, high defensive rating, medium pace, and is experienced, the probability of losing is 43.0%.

• Rule 17:

- Conditions: MIN==Medium & OFFRTG==High & DEFRTG==Low & PACE==Medium & YOE==Experienced
- o Result: WIN=Not Win (0.25)
- Explanation: If a player has medium playing time, a high offensive rating, low defensive rating, medium pace, and is experienced, the probability of losing is 25.0%.

• Rule 18:

- Conditions: MIN==Medium & OFFRTG==Medium & DEFRTG==Medium & PACE==Medium & YOE==Veteran
- o Result: WIN=Not Win (0.406)
- Explanation: If a player has medium playing time, a medium offensive rating, medium defensive rating, medium pace, and is a veteran, the probability of losing is 40.6%.

• Rule 19:

- Conditions: MIN==Medium & OFFRTG==Medium & DEFRTG==Medium & PACE==Low & YOE==Experienced
- o Result: WIN=Not Win (0.473)
- Explanation: If a player has medium playing time, a medium offensive rating, medium defensive rating, low pace, and is experienced, the probability of losing is 47.3%.

• Rule 20:

- Conditions: MIN==Medium & OFFRTG==Very Low & DEFRTG==Very High & PACE==Medium & YOE==Experienced
- o Result: WIN=Not Win (0.38)
- Explanation: If a player has medium playing time, a very low offensive rating, very high defensive rating, medium pace, and is experienced, the probability of losing is 38.0%.

• Rule 21:

- Conditions: MIN==Medium & OFFRTG==Low & DEFRTG==High & PACE==Medium & YOE==Experienced
- o Result: WIN=Win (0.44)
- Explanation: If a player has medium playing time, a low offensive rating, high defensive rating, medium pace, and is experienced, the probability of winning is 44.0%.

• Rule 22:

- Conditions: MIN==High & OFFRTG==Medium & DEFRTG==Medium & PACE==Low & YOE==Veteran
- o Result: WIN=Not Win (0.44)
- Explanation: If a player has high playing time, a medium offensive rating, medium defensive rating, low pace, and is a veteran, the probability of losing is 44.0%.

Rule 23:

- o Conditions: MIN==Medium & OFFRTG==Very Low & DEFRTG==Very High
- o Result: WIN=Not Win (0.7)
- Explanation: If a player has medium playing time, a very low offensive rating, and very high defensive rating, the probability of losing is 70.0%.

Rule 24:

- o Conditions: MIN==High & OFFRTG==Very High
- o Result: WIN=Win (0.7)
- Explanation: If a player has high playing time and a very high offensive rating, the probability of winning is 70.0%.

• Rule 25:

- o Conditions: MIN==High & OFFRTG==High
- o Result: WIN=Win (0.6)
- Explanation: If a player has high playing time and a high offensive rating, the probability of winning is 60.0%.

Rules have been adapted to include YOE considering that being experienced is something with a positive influence on the results, given not only his performance but the positive impact in team organization and intelligence. Apart from this, rules 23 to 25 were introduced to consider what happens when a top player stays in the court for a long time. The symmetric rules for those with high offensive rating haven't been considered because their bad performance can be compensated by the rest of the team. To get a better understanding about how rules were selected, see [1].

Implementation of the System

The theoretically described Fuzzy System has been implemented on MATLAB R2022b using Fuzzy Logic Designer Application using Mamdani Type 1 problem representation.

In this Application, the input-output structure can be clearly visualized in the diagram shown in Figure 8 and block of rules is defined in the way represented in Figure 9. Finally, results can be analysed using *Control Surface* and *Rule Inference* tools.

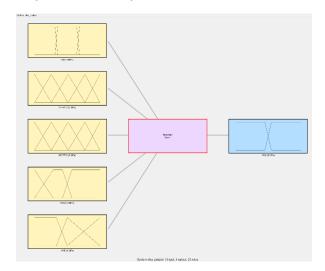


Figure 8: Design Implementation in MATLAB

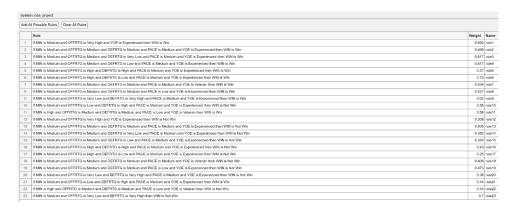


Figure 9: Rule definition in MATLAB

Control surfaces for the most important variables, i.e., OFFRTG and DEFRTG, show interesting outputs. These outputs for WIN are between 40 and 75 (see Figure 11 top-left). The reason is the use of realistic information, given that the presence of a specific player can't determine completely for the victory of the team.

Comparing OFFRTG and DEFRTG again WIN, the results are meaningful from a basketball match point of view. If average points scored by the team when the player is on the court is very low (OFFRTG equal to 90) and the average number of points scored by the opponent is very high (DEFRTG equal to 125) then, probability of winning the match gets reduced to the minimum. However, when OFFRTG increases these chances increase substantially, being this variable the most important one in order to consider how crucial the player is for the victory of the team.

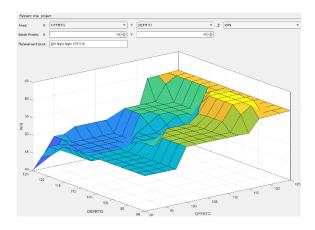


Figure 10: Control Surface for OFFRTG and DEFRTG

When the number of played minutes is medium or high and the offensive rating of the player is from high to very high, then the probability of winning increases significantly. In the case of possession, when offensive rating is high, probabilities of winning are on 60% independently of the PACE. When PACE is low, even for medium offensive rating, some improvement can be seen. This is because if a medium quality player doesn't lose possession, then probabilities of winning are slightly increased. Finally, the relationship between years of experience (YOE), offensive rating (OFFRTG) and WIN is very insightful. A high experienced player, even with medium OFFRTG, can increase probabilities of winning even a 6%.

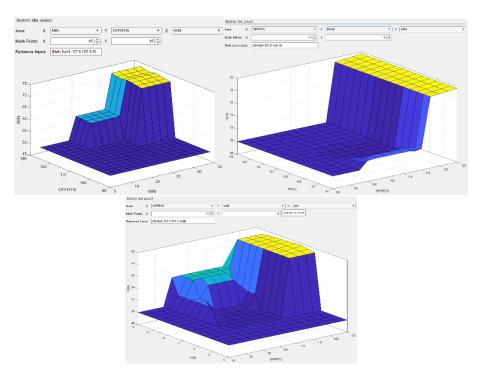


Figure 11: Control Surfaces for each Variable against OFFRTG

In the case of defensive rating (DEFRTG), experienced players with low defensive rating increase probability of winning given their expertise and that they aren't scored against very often. If PACE is high, then even if defensive rating is low, the loss of possession penalizes and probability of winning falls to 47%. At the same time, if DEFRTG is low and PACE is also low, then we have a player who is defensively strong and difficult to steal the ball to. Finally, a strongly defensive player increases probability of victory for an intermediate amount of minutes.

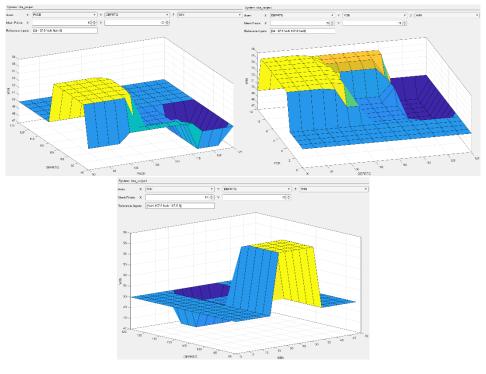


Figure 12: Control Surfaces for each Variable against DEFRTG

Test Cases

Information about the players has been extracted from [2]. Many different metrics are available, allowing us to check and try different variables and a wide rage of examples for the ones already selected.

Lebron James (Top class player)

In his best season (08/09) his offensive rating was 122 and his defensive rating 99. These measurements are taken by 100 possessions so, for simplicity, we consider PACE 100. In this season, his experience was 4 years.

Variable	Value	Activation
OFFRTG	122	Very High
DEFRTG	99	Low
PACE	100	Medium
YOE	4	Novice

Low number of minutes (1 quarter)

Let's analyse what happens when a star plays just one quarter.

Variable	Value	Activation
MIN	12	Low
OFFRTG	122	Very High
DEFRTG	99	Low
PACE	100	Medium
YOE	4	Novice

The probability of winning is 50%, i.e., it doesn't affect the game. The main reason as it can be observed from Figure 12, is that MIN isn't activated for rules 24 and 25, which have a high weight (0.6 - 0.7) in favour of WIN in the case of the player having a high or very high OFFRTG.

High number of minutes (whole match)

Let's analyse what happens when Lebron James plays the whole match.

Variable	Value	Activation
MIN	48	High
OFFRTG	122	Very High
DEFRTG	99	Low
PACE	100	Medium
YOE	4	Novice

In this case, rules 24 and 25 get activated, providing a high chance of winning: 73.5%.

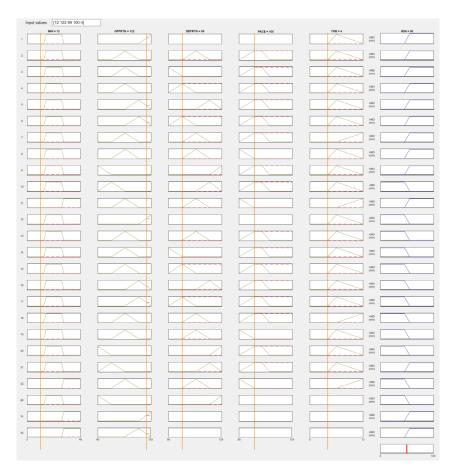


Figure 13: Results for Lebron James playing one quarter

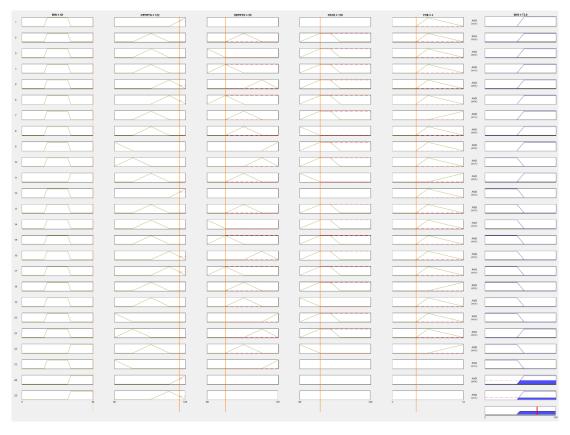


Figure 14: Results for Lebron James playing the whole match

Jordan Poole

This is one of the players with the worst statistics in NBA. In his worst season (23/24) his numbers are the following ones

Variable	Value	Activation
MIN	24	Medium
OFFRTG	94	Very Low
DEFRTG	124	Very High
PACE	100	Medium
YOE	4	Novice

Jordan is a novice with bad statistics playing a medium number of minutes. As could be expected, probabilities of winning in his case are extremely low: 24%

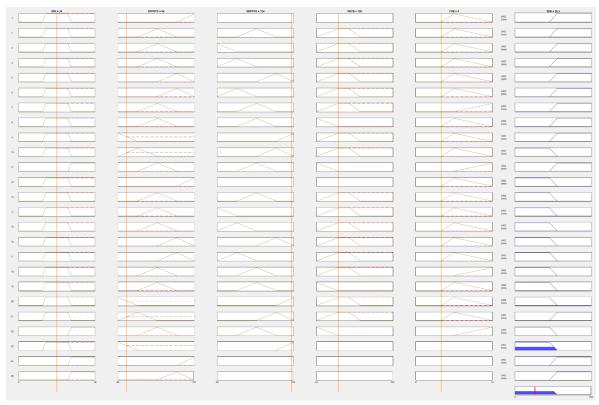


Figure 15: Results for Jordan Poole

Michael Jordan

Season 90/91

This NBA legend 's best season was the 90/91.

Variable	Value	Activation
MIN	24	Medium
OFFRTG	125	Very High
DEFRTG	102	Low
PACE	100	Medium
YOE	6	Experienced

In this case, a young but with some experience player playing only the half of the match increases the chances of winning to 74.4%. This can be reached only by the best player in NBA history.



Figure 16: Results for Michael Jordan season 90/91

Season 95/96

Michael Jordan kept having amazing stats 5 years later.

Variable	Value	Activation
MIN	24	Medium
OFFRTG	124	Very High
DEFRTG	100	Low
PACE	100	Medium
YOE	11	Veteran

In this case, the system provides a 63.7% of chances of winning. The reason is that he is considered to be too veteran, activating the rules weakly in the AGE variable.



Figure 17: Results for Michael Jordan season 95/96

Wendell Carter Jr

This is an average player who hasn't any special characteristics. We expect him not to be decisive.

Variable	Value	Activation
MIN	24	Medium
OFFRTG	112	High
DEFRTG	112	High
PACE	100	Medium
YOE	5	Novice-Experienced

He is balanced and if he plays more minutes, his high offensive rating can be fundamental to get the victory of his team. As observed in Figure 17, he hasn't any influence in the victory of the team in a bad or in a positive way. The rules activated in this case are 2, 5, 13 and 16. The two first rules push the result in the direction of increasing WIN while 13 and 16 do it in the opposite direction with the same strength. This leads to no global effect.



Figure 18: Results for Wendell Carter Jr

Improved model

The previously built model has some weaknesses that can be easily solved just by including new features and introducing hierarchical relationships among them. It was observed that there are some asymmetries between OFFRTG and DEFRTG because bad defensive actions can be compensated by the rest of the team, given that it doesn't imply necessarily losing the possession. However, in most of the cases, badly executed offensive actions carries possession loss and then, the influence of the rest of the team in fixing this is lower. This is why 2 different blocks have been designed: performance of the player and performance of the team. In addition to this, player profile is more complex than only the number of points scored/allowed while he is on court. This is the reason why a more complete player description is provided, dividing player performance in offensive, defensive and game distribution properties. Each of these categories, is at the same time composed by the blocks seen in Fig. 18.

Inputs:

- Points per game (PPG): Representing the player's offensive output.
- Rebounds per game (RPG): Reflecting the player's ability to grab rebounds and control the boards.

- Assists per game (APG): Illustrating the player's ability to distribute the ball and create scoring opportunities for teammates.
- Field goal percentage (FG%): Representing the player's efficiency in making shots from the field.
- Three-point field goal percentage (3P%): Demonstrating the player's accuracy in making shots from beyond the arc.
- Defensive rating (DEFRTG): Representing the player's ability to limit the opposing team's scoring.
- Turnover percentage (TO%): Reflecting the player's ball-handling skills and tendency to commit turnovers.
- Years of experience (YOE): Reflecting the player's tenure in the league and accumulated knowledge and skills.
- Minutes played per game (MIN): Representing the player's role in the team's offensive and defensive schemes.
- Possession (PACE): Representing the number of possessions in the match.
- Coaching experience (CXE): Reflecting the coach's experience and ability to manage the team and motivate the players.
- Team's offensive rating (TORT): Representing the team's overall offensive efficiency.
- Team's defensive rating (TDEFRTG): Representing the team's overall defensive effectiveness.

Outputs:

• Winning percentage (WP): Predicting the player's contribution to the team's overall performance and winning probability.

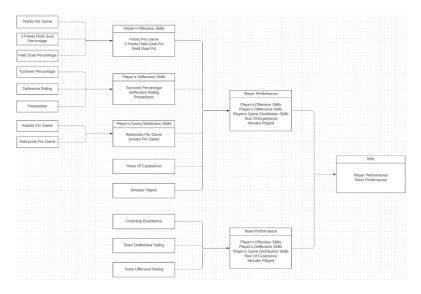


Figure 19: Hierarchical Expert System Design

The proposed fuzzy expert system is a more comprehensive, accurate, interpretable, and transparent tool for assessing basketball player performance compared to the previous one with the cost of extra complexity in terms of computation, testing and debugging.

Conclusion

In conclusion, the development of a fuzzy expert system for estimating basketball player performance represents a significant step forward in the field of sports analytics. This work draws inspiration from previous research on Bayesian networks [1] and expands upon it by introducing a fuzzy logic-based model. The system is designed to predict a basketball player's winning percentage based on a set of carefully selected input variables, including offensive and defensive ratings, possession, years of experience, and minutes played.

The process involves defining linguistic variables, designing membership functions, and formulating rules that capture the complex relationships between these variables. The results presented in this work demonstrate the impact of various input factors on the winning percentage, providing valuable insights for both player evaluation and strategic decision-making. The system's rules are derived from a combination of statistical analysis [1] and additional rules for completeness.

The implementation of the fuzzy system using MATLAB showcases the practical application of the theoretical framework. Control surfaces for key variables, such as offensive and defensive ratings, reveal the nuanced influence of these factors on the predicted winning percentage. Test cases featuring well-known players like LeBron James and Michael Jordan further validate the system's capability to assess player performance under different scenarios.

To enhance the model's versatility, an improved version is proposed, incorporating a broader set of input variables, such as points per game, rebounds per game, and coaching experience. This more complex system aims to provide a more comprehensive and accurate assessment of player contributions, considering a wider range of factors that influence team performance.

In summary, the fuzzy expert system presented in this work offers a valuable tool for assessing basketball player performance, providing a nuanced and interpretable analysis. While the enhanced model introduces greater complexity, it promises a more refined understanding of player contributions and the potential for broader applications in basketball-related tasks.

References

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