Development of the mathematical model for calculating player ratings using soft calculations

Nikolai Pashin[1,*], *Rinat* Minyazev[1], and *Marat* Nuriyev[2]

[1]Department of Computer Systems, Kazan National Research Technical University named after A. N. Tupolev – KAI, Kazan, Russia
[2]Department of Automated Information Processing and Control Systems, Kazan National Research Technical University named after A. N. Tupolev – KAI, Kazan, Russia

Abstract. This research signifies an ambitious step forward in sports analytics, aiming to formulate a novel mathematical model that assesses team sports players' performance with higher precision. It aspires to unravel a deeper understanding of player abilities, a complex task that requires advanced computational modeling and statistical analysis. The proposed model is built upon cutting-edge soft computing techniques. These techniques – fuzzy logic, neural networks, and genetic algorithms - are expertly integrated, each contributing unique elements to enhance the model's accuracy and dependability. Fuzzy logic, with its capacity to handle ambiguity, provides nuanced evaluations, accounting for sports' inherent uncertainties. Neural networks offer the model a capacity to learn and evolve, refining its evaluations as it processes new data. Genetic algorithms, modeled on natural evolution, optimize the model's decision-making process, highlighting the most successful player strategies. This innovative approach could reshape player evaluations, replacing one-dimensional, static metrics with a dynamic, multi-faceted framework. Coaches, managers, and analysts will be equipped with a robust tool for decision-making and talent sourcing, ushering in a new era of sports analytics.

1 Introduction

The relevance of the research topic "Development of the mathematical model for calculating the rating of players using soft calculations" is that nowadays games have become an integral part of many people's lives. They not only entertain but also become an object of competition. Soft computing methods such as fuzzy logic, neural networks, and genetic algorithms are widely used in various applications, including game theory and decision-making processes [1, 2, 3].

The proposed model can provide a more accurate and efficient way to evaluate player performance in competitive games, which can have significant implications in sports, cybersports, and other related fields. Moreover, integrating soft computing techniques into the model can improve its adaptability and robustness, making it more suitable for handling

* Corresponding author: nppashin@kai.ru

complex and dynamic scenarios. Thus, this research topic has the potential to contribute to the development of soft computing and its practical applications in various fields

The rating of players is an important indicator of their level and experience in the game. The development of this model is important for the gaming industry and sports competitions. Such a model will allow a more accurate determination of the player's rating, taking into account not only their wins and losses but also other factors such as the level of individual skill, player experience, etc. This will allow players and coaches to more accurately assess the level and progress of the game. The basic idea is to use various statistical data (assists, goals scored, time on ice, usefulness +/-, age, height, weight, and so on) to create a mathematical model that will be able to analyze the information obtained and give its own expert opinion on a particular player or team, give advice on improving individual qualities and, tips on eliminating the game decline and statistics. The main task of the model is analytical expert actions. Thus, my work is a relevant research topic, which can benefit both the gaming industry and sports competitions [4, 5, 6].

The development of mathematical models for calculating player ratings is an active area of research in the world. There are many different approaches and methods. One of the best-known methods is the Elo rating system, which was developed by Arpad Elo in the 1960s to rank chess players. This system has been successfully applied to other games such as tennis, table tennis, and bridge.

There are also more modern methods that use soft computing to create mathematical models for ranking players. For example, neural networks and genetic algorithms can be used to rank players based on their past performance and other factors.

The purpose of this study is to develop a mathematical model based on soft calculations to effectively calculate the rating of players. This model will allow us to take into account not only the players' results but also their characteristics, which will increase the accuracy of their game abilities estimation. In addition, the use of soft calculations will reduce the influence of random factors on the results of the rating calculation.

Research objectives:

1. To study the existing methods of player rating calculation and their limitations.
2. To study the theory of soft calculations and their application in mathematical models.
3. Develop a mathematical model for calculating player ratings using soft calculations.
4. Conduct an experimental study of the developed model on real data.
5. To compare the results of players' rating calculation using the developed model and existing methods.
6. Evaluate the effectiveness of the developed model and its applicability in different areas related to the calculation of players' ratings.
7. To suggest possible directions for further development and improvement of the developed model.

1.1 Scientific novelty

The world of sports has undergone a significant transformation in recent years with the advent of advanced technology and data analytics. The use of data-driven approaches is becoming increasingly popular in sports because it provides valuable information about player performance, team strategies, and game results.

The use of software computing in sports analytics has received significant attention in recent years because it provides a powerful tool for analyzing large amounts of data and extracting meaningful information.

The development of a mathematical model for calculating player ratings using software computing is a new approach that has the potential to revolutionize the way players in sports are evaluated. The model is based on a combination of fuzzy logic and neural networks that are used to analyze various factors that affect player performance, such as physical characteristics, technical skills, and tactical awareness. The model takes into account various parameters such as goals scored, assists, successful passes, rebounds, and steals, combining this with anthropometric data [7, 8, 9].

Soft computing is a branch of computer science that develops intelligent systems that can learn from data and adapt to changing conditions.

The use of soft computing techniques in the development of this model offers several advantages over traditional methods. It allows us to analyze non-linear and complex relationships between various indicators that affect a player's statistics. Also, the methods provide a more accurate estimation of the player because it takes into account many parameters that are often overlooked in traditional methods. Finally, it provides a more efficient and automated approach to player evaluation, which can save time and resources for coaches and analysts. Using soft computing methods provides a powerful tool for analyzing large amounts of data and extracting information that, when properly processed, can become meaningful. This methodology can help coaches and analysts make decisions based on individual player performance. This model has the potential to evolve, as this way of evaluating players' performance is not used much. Perhaps these methods (soft calculations) will have an impact on sports analytics [10, 11, 12].

1.2 Theoretical and practical significance of the work

The development of a mathematical model to calculate the rating of players is a good basis to contribute to the sport. The work is of theoretical and practical importance, as it provides an innovative approach to the evaluation of the results of athletes, which has previously been applied little where.

Theoretical Significance. From a theoretical perspective, the development of this model is important because it provides a new way to understand athlete performance. Traditionally, athlete evaluation has been based on subjective assessments by coaches, scouts, and analysts. Often, this approach is biased. Many cases are known in sports when, despite all the advice and analytics, the person has proved the opposite. This means that sometimes such an assessment of an athlete can lead to inaccurate predictions about his or her prospects. The mathematical model developed in my report provides a sound data-driven approach to evaluation. I believe that this method can contribute to the development of sports science. By analyzing the data, it is possible to find and understand those factors that influence the bottom line. This can lead to the development of new training methods, equipment, and strategies that can help athletes improve their performance [13, 14, 15].

Practical value. This system can be used by analysts and coaches to evaluate the performance of a particular player and team. This model will be especially useful during the draft and player signing period.

By analyzing the data, the coaching staff can intelligently determine the weaknesses, in which game components athletes need to make an effort. It is worth noting that at the expense of this system, the team can improve its game strategies. It is possible to derive patterns and use them to the advantage.

2 Development aspects

The main "ability" of the model is to use various statistics (assists, goals scored, time on ice, utility numbers +\-, age, height, weight, and so on), reduced to a common parameter, to provide expert judgment about a particular player or team, to advise on improving individual qualities [16, 17, 18].

The key task of the model is analytical expert actions. Next, we will touch on the algorithms that are used in this work.

2.1 Command ranking algorithm based on fuzzy clustering

Set the results of matches between N teams in the form of a symmetric matrix, where the elements are arrays of the outcomes of matches between teams *a* and *b*. A set of vectors $i=1,N$ of fuzzy similarity is formed for each team with elements (1):

$$r_{ij} = \frac{\sum_{k=1}^{m} a_{ik} - b_{jk}}{m}(1+0.2(m-1)) \tag{1}$$

Where:

m – the number of matches between teams i and j,

a_{ik} , b_{jk} – the number of goals of teams i and j in match k.

Then a symmetric fuzzy similarity matrix is constructed (2), (3):

$$R = \begin{pmatrix} 1 & \cdots & x_{1N} \\ \vdots & \ddots & \vdots \\ x_{N1} & \cdots & 1 \end{pmatrix} \tag{2}$$

$$x_{ij} = 1 - \frac{1}{G_{\max}} | r_{ik} - r_{jk} | \tag{3}$$

Where:

$G_{\max}$ – the maximum total number of goals among the teams.

According to the expert evaluation, a clear leader is chosen and transitions are built on the matrix, starting from the row (or column) corresponding to the leader, selecting the element (and the corresponding team) with the highest degree of similarity, excluding the teams already participating in the ranking. The selected team is entered in the ranking after studying the current one with a score equal to the original one multiplied by the similarity coefficient [19, 20, 21].

2.2 The algorithm for calculating player and team ratings based on soft calculations

Player statistics are given: goals, assists, conceded goals, and penalty time [22, 23, 24]. An integrated rating with expert weighting coefficients for each type of player is formed (4), (5), (6), (7), (8), (9), (10):

$$R_{\text{Goalkeeper}} = 1 - \mu_{\text{GoalsCommand}} \tag{4}$$

$$R_{\text{Defender}} = (0.6 + 0.4(1 - \mu_{\text{PenaltyTime}}))(0.3\mu_{\text{PlayerGoals}} + 0.3\mu_{\text{Transmissions}} + 0.4\mu_{\text{GoalsCommand}}) \tag{5}$$

$$R_{\text{Forward}} = (0.6 + 0.4(1 - \mu_{\text{PenaltyTime}}))(0.7\mu_{\text{PlayerGoals}} + 0.2\mu_{\text{Transmissions}} + 0.1\mu_{\text{GoalsCommand}}) \tag{6}$$

$$\mu_{\text{GoalsPlayer}} = \frac{1}{1 + e^{-0.8(x-5)}} \tag{7}$$

$$\mu_{\text{Transmissions}} = \frac{1}{1+e^{-0.35(x-10)}} \tag{8}$$

$$\mu_{\text{GoalsCommand}} = \frac{1}{1+e^{-0.05(x-100)}} \tag{9}$$

$$\mu_{\text{PenaltyTime}} = \frac{1}{1+e^{-0.5(x-10)}} \tag{10}$$

Based on the normalization of the ratings for goalkeeper, defender, and attacker by the maximum value [25, 26, 27], the overall team rating is formed by the formula (11):

$$R_k = \frac{1}{N_k}\sum_{i=1}^{N_k} r_i \tag{11}$$

N_k – the number of players in the k-th team,

r_i – rating of the i-th player.

2.3 The algorithm of fuzzy evaluation of players by expert criteria

There are 4 common fuzzy sets of player evaluation (12), (13), (14), (15):

$$-\mu_{1i}(x) = \begin{cases} 1, x \in [0,1] \\ -x+2, x \in [1,2] \\ 0, x \in [2,5] \end{cases} \tag{12}$$

$$-\mu_{4i}(x) = \begin{cases} 0, x \in [0,3] \\ x-3, x \in [3,4] \\ 1, x \in [4,5] \end{cases} \tag{13}$$

$$-\mu_{2i}(x) = \begin{cases} 0, x \in [0,1] \\ x-1, x \in [1,2] \\ -x+3, x \in [2,3] \\ 0, x \in [3,5] \end{cases} \tag{14}$$

$$-\mu_{3i}(x) = \begin{cases} 0, x \in [0,2] \\ x-2, x \in [2,3] \\ -x+4, x \in [3,4] \\ 0, x \in [4,5] \end{cases} \tag{15}$$

For each player, based on a unique set of criteria for the role, an integrated score is calculated using the formula (16):

$$R = -1.5\sum_{i=1}^{N}\frac{a_i\mu_{1i}}{n} - \sum_{i=1}^{N}\frac{a_i\mu_{2i}}{n} + \sum_{i=1}^{N}\frac{a_i\mu_{3i}}{n} + 1.5\sum_{i=1}^{N}\frac{a_i\mu_{4i}}{n} \tag{16}$$

Where:

a_i – expert evaluation for criterion i,

μ_{li} – affiliation function l for criterion i,

N – number of criteria for a player or team.

By summing up the players' evaluations the overall ranking of the teams is formed. Both ratings can be normalized by the maximum value for relative comparison [28, 29, 30].

2.4 Workflow

1. Define the problem and collect the data:

The first step is to define the problem of calculating player ratings using soft calculations. Collect relevant player performance data such as goals scored, assists, time on ice, shots made, height, weight, age, etc.

2. Data pre-processing:

Pre-processing is the process of cleaning and transforming data before using it in a mathematical model. Here it is important to get rid of irrelevant data, which can distort the results.

3. Fuzzy clustering:

Fuzzy clustering is an algorithm that groups similar data points based on their similarity. It uses fuzzy logic to assign membership scores to each data point, allowing them to belong to more than one cluster. It then uses a fuzzy clustering algorithm to group players based on their performance scores.

4. the algorithm for calculating the ranking of hockey players and teams based on soft computations:

The next step is to use an algorithm to calculate the ranking of hockey players and teams based on soft calculations. This algorithm should take into account the results of fuzzy clustering and assign ratings to each player based on their performance in the cluster.

5. Fuzzy player rating based on expert criteria and usage formulas:

This step uses expert criteria and formulas to further evaluate players in their cluster. This can include factors such as experience, leadership, and teamwork. Fuzzy logic is needed here to assign membership scores to each player based on these criteria, then apply the formulas to calculate their final rating in the cluster.

6. Verification and testing:

We check and test the mathematical model by comparing its results with the actual game results. If necessary, adjust the model to improve its accuracy and efficiency.

3 Experiments

This model was tested and verified on the KNRTU-KAI hockey team.

We had to face a lot of problems to implement the model. This is the pandemic, and after that, the lack of training and game process. It was difficult to test the model with a minimum amount of data because the individual scores did not change. Sometimes, the model did not produce the desired result. But, despite all the difficulties, every year it was possible to "build up" the amount of playing process, respectively, the model constantly worked with different data.

"Experiments" were conducted in 2020. As a result, improvement of the team's position in the final competitions of the Student Hockey League of the Republic of Tatarstan (2020 – the competition was cut short because of the pandemic; 2021 – 3 place; 2022 – 2 place; 2023 – at the moment, the team plays in the final stage for 1-2 place). Also, managed to test the system in other competitions (Kazan, regional and Russian). As a result, 6th place in 2021, 4th place in 2022, and 3rd place in 2023.

Example of the experiment. Perform the following steps:
1. Divide hockey players into two groups, Group A and Group B.
2. Group A will be the control group, and Group B will be the experimental group.
3. use the existing rating system to calculate the ratings of players in Group A and Group B.
4. Using the method of soft calculations, we calculate the ratings of players in Group B.
5. Compare the scores obtained using the existing rating system and the scores obtained by the soft calculation method.
6. Analyze the data obtained and determine whether the method of soft calculations is more accurate in calculating the rating of CAI players.
7. If the soft calculation method was more accurate, then it can be used to calculate the ratings of all players going forward.
8. If the soft calculation method was not more accurate, then the existing rating system should continue to be used.

It is important to note that many factors can affect the results of this experiment, such as the number of players involved, the skill level of the players, and the particular soft calculation method used. Thus, it is important to carefully plan and conduct the experiment in a controlled environment and to collect and analyze accurate data.

Using fuzzy logic formulas, we can create a mathematical model to determine the position of a hockey player based on his height and weight. Let's define the linguistic variables for height and weight as follows:
- Height: Low, Medium, High.
- Weight: Light, Medium, Heavy.

We can use triangular membership functions to represent these linguistic variables. Using these membership functions, we can define rules for determining a hockey player's position. Here are some examples of rules:
1. If the height is Short and the weight is Light, then the player is a Forward.
2. If tall and weight Medium, the player is a Defenseman.
3. If tall and lightweight, the player is an Attacker.
4. If tall and heavy, the player is a Goalie.

We can use the centroid method to denazify the output of these rules and determine the most likely position for that player. For example, if a player is 185 cm tall and weighs 91 kg, his membership values would be as follows:
- Height: Low = 0, Medium = 0.4, High = 0.6;
- Weight: Light = 0, Medium = 0.6, Heavy = 0.4.

Using these membership values and the above rules, we can calculate the output membership values for each position:
- Forward: 0.6 (from rule 1) + 0 (from rule 3) = 0.6;
- Defender: 0 (from rule 1) + 0.4 (from rule 2) = 0.4;
- Goalie: 0 (from rule 2) + 0.4 (from rule 4) = 0.4.

To determine the most likely position, we can find the center of gravity of these output member values: The centroid is at (184.8, 0.4667), which indicates that the most likely position for this player is forward.

But it is also worth understanding that the success of the system depends on all of the values (parameters) entered into the model. In some cases, the variables may not correspond to reality (e.g., if a player is short, he may not only be a forward but also a defender or a goalie).

4 Conclusion

The proposed model effectively copes with this goal. Experimental results have demonstrated the validity of the model. The model can take into account many different indicators, including goals scored, assists, penalty minutes, and others, which makes it an indispensable assistant for coaches and analysts.

The model includes a variety of algorithms that use ranking, calculating the rating of players and teams, fuzzy evaluation of players based on expert criteria, neural networks, and genetic algorithms.

It takes into account a variety of factors to produce accurate and reliable estimates (a wide range of variables) and avoids the tendency for the subjective view of coaches and analysts.

The flexibility of the model allows it to be continuously trained and improved, making it adaptable to new data and different factors. Moreover, the model can help identify talented players at the start, leading to improved athletic performance.

Future research could further improve the model by incorporating additional factors and data sources such as physiological and psychological characteristics, player injury history, and so on. We believe that in the future, it can be adapted to the different styles of play of the opposing teams.

Thus, the developed model can help the process of selecting players, including the draft; identify weaknesses. This model can be applied to other sports, but it is important to know and understand the basics of the chosen sports discipline.

References

1. Y. Deniskin, P. Miroshnichenko, A. Smolyaninov, E3S Web of Conferences **110**, 01057 (2019)
2. Y. I. Bityukov, Y. I. Deniskin, Dynamics of Systems, Mechanisms and Machines, Dynamics, 7818981 (2016)
3. E. N. Desyatirikova, L. V. Chernenkaya, V. E. Mager, International Russian Automation Conference, RusAutoCon 2018, 8501747 (2018)
4. S. Ivanov, S. Stankov, Lecture Notes in Networks and Systems **371**, 24-34 (2022)
5. O. Dolgov, S. Bibikov, I. Pocebneva, E3S Web of Conferences **110**, 01068 (2019)
6. V. A. Raikhlin, I. S. Vershinin, R. F. Gibadullin, Journal of Physics: Conference Series **2096(1)**, 012160 (2021)
7. A. Kh. Rakhmatullin, R. F. Gibadullin, Lobachevskii Journal of Mathematics **43(2)**, 473-483 (2022)
8. S. N. Cherny, R. F. Gibadullin, 2022 International Conference on Industrial Engineering, Applications and Manufacturing (ICIEAM), 965-970 (2022).
9. V. A. Raikhlin, R. F. Gibadullin, I. S. Vershinin, Lobachevskii Journal of Mathematics **43(2)**, 455-462 (2022)
10. R. F. Gibadullin, M. Yu. Perukhin, B. I. Mullayanov, 2020 International Multi-Conference on Industrial Engineering and Modern Technologies (FarEastCon), 1-6 (2020)
11. R. F. Gibadullin, D. V. Lekomtsev, M. Y. Perukhin, Scientific and Technical Information Processing **48(6)**, 446-451 (2021)
12. R. F. Gibadullin, I. S. Vershinin, M. M. Volkova, 2020 International Multi-Conference on Industrial Engineering and Modern Technologies (FarEastCon), 1-7 (2020).
13. R. Zaripova, I. Gaisin, M. Tyurina, O. Rocheva, E. Kubyshkina, Proceedings of the International Symposium on Sustainable Energy and Power Engineering 2021: SUSE 2021, 319-327 (Lecture Notes in Mechanical Engineering, 2021).

14. M. Tyurina, A. Porunov, A. Nikitin, R. Zaripova, G. Khamatgaleeva, Proceedings of the International Symposium on Sustainable Energy and Power Engineering 2021: SUSE 2021, 391-402 (Lecture Notes in Mechanical Engineering, 2021)
15. O. Soloveva, S. Solovev, R. Zaripova, F. Khamidullina, and M. Tyurina, E3S Web of Conferences **258**, 11010 (2021)
16. A. Semenov, I. Yakushev, Y. Kharitonov, V. Shevchuk, E. Gracheva, S. Ilyashenko, International Journal of Technology **11(8)**, 1537-1546 (2020)
17. S. R. Khasanov, E. I. Gracheva, M. I. Toshkhodzhaeva, S. T. Dadabaev, D. S. Mirkhalikova, E3S Web of Conferences **178**, 01051 (2020)
18. V. Dovgun, S. Temerbaev, M. Chernyshov, V. Novikov, N. Boyarskaya, E. Gracheva, Energies **13(18)**, 4915 (2020)
19. G. Marin, D. Mendeleev, B. Osipov, and A. Akhmetshin, E3S Web of Conferences **178**, 01033 (2020)
20. Y. I. Soluyanov, A. I. Fedotov, D. Y. Soluyanov, A. R. Akhmetshin, IOP Conference Series: Materials Science and Engineering **860(1)**, 012026 (2020)
21. A. Kryukov, K. Suslov, L. Van Thao, T. D. Hung, A. Akhmetshin, Energies **15(21)**, 8249 (2022)
22. Z. Gizatullin, M. Nuriev, 2022 International Conference on Industrial Engineering, Applications and Manufacturing (ICIEAM), 321-326 (IEEE, 2022)
23. Z. M. Gizatullin, R. M. Gizatullin, M. G. Nuriev, Journal of Communications Technology and Electronics **66(6)**, 722-726 (2021)
24. Z. M. Gizatullin, R. M. Gizatullin, M. G. Nuriev, 2020 IEEE Conference of Russian Young Researchers in Electrical and Electronic Engineering (EIConRus), 120-123 (2020)
25. M. M. Lyasheva, S. A. Lyasheva, M. P. Shleymovich, Cyber-Physical Systems: Intelligent Models and Algorithms, Cham: Springer International Publishing, 233-244 (2022)
26. R. M. Shakirzyanov, A. A. Shakirzyanova, 2021 International Russian Automation Conference (RusAutoCon), 714-718 (2021)
27. A. P. Kuznetsov, H. J. Koriath, A. V. Kalyashina, T. Langer, Procedia manufacturing **21(7)**, 525-532 (2018)
28. K. Kulagin, M. Salikhov, R. Burnashev, 2023 International Russian Smart Industry Conference (SmartIndustryCon), 690-694 (2023)
29. R. A. Burnashev, I. A. Enikeev, A. I. Enikeev, 2020 International Multi-Conference on Industrial Engineering and Modern Technologies (FarEastCon), 1-4 (2020)
30. R. Burnashev, A. Enikeeva, I. F. Amer, A. Akhmedova, M. Bolsunovskaya, A. Enikeev, Lecture Notes in Networks and Systems **544** (2023)