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Yelyzaveta HNATCHUK, Tetiana HOVORUSHCHENKO, Alina HNATCHUK

Khmelnytskyi National University, Khmelnytskyi, Ukraine

METHOD OF RANKING ATHLETES IN A DECISION SUPPORT SYSTEM IN THE PROCESS OF PRELIMINARY SELECTION OF PLAYERS

The topic of the article *is the method of ranking athletes in a decision support system in the process of preliminary selection of players.* ***The purpose of the*** *is to develop an athlete ranking method that enables the integration of all available information types, facilitating informed decision-making, as selection accuracy directly impacts the quality of the resulting team.* ***Research objectives:*** *investigate the information types utilized in athlete ranking and identify appropriate methods for data representation and processing; to develop a method based on specific metrics, production rules, weighting coefficients, and an artificial neural network (ANN) model to generate player ratings within a DSS; to conduct an experiment to validate the effectiveness of the proposed method.* ***Research results:*** *The article proposes a hybrid ranking method that integrates a deterministic component (IF-THEN production rules) with an adaptive ANN model. This architecture combines expert heuristic knowledge with automated data-driven learning, ensuring both decision explainability and the model's robustness in complex conditions. At the first level, the system ranks candidates using predefined logical rules derived from expert assessments by coaches and analysts. These rules process formalized metrics such as physical development, fitness, and competition history, enabling initial screening based on basic functional suitability criteria for a specific position. At the second level, an ANN module is integrated to perform a multidimensional analysis of the players' numerical characteristics. By identifying latent non-linear dependencies between tactical and technical action indicators and anthropometric variables, the model provides a predictive assessment of overall potential. This approach is particularly effective in scenarios where manually formulated rules cannot capture the complex interdependencies between variables. The final output integrates a binary classification (fit/unfit) with a quantitative rating generated by the neural network. These results can be mapped to a formalized scale for further ranking or utilized as primary input for final coaching decisions. This structure ensures an optimal balance between interpretability, accuracy, and adaptability within the volleyball player selection process.* ***Conclusions:*** *The scientific novelty lies in combining a structured system of TTA indicators with role-specific weighting obtained through expert consensus, allowing for contextual adaptation. Additionally, the integration of a neural network component to identify latent dependencies between performance indicators dynamically represents a novel approach for short-term selection in volleyball.* ***Further research*** *will focus on developing adaptive player models and optimizing selection processes to enhance the effectiveness of decision-making within the DSS.*

Keywords: *decision support system; decision-making; decision-making criteria; ranking method; rules; artificial neural networks; preliminary selection of players.*

1. Introduction

1.1. Motivation

The rapid advancement of intelligent information systems and technologies has rendered them ubiquitous across virtually all domains. As the sports industry evolves, these technologies are increasingly employed to enhance the efficiency of data processing for sports managers and scouts. In particular, they enable match outcome prediction, support coaching staff in decision-making under conditions of uncertainty, and facilitate the organization of competitions, training processes, and the provision of sports services.

Currently, athlete selection for national teams or club competitions in team sports such as volleyball, basketball, and football is a complex and labor-intensive process requiring effective decision-making. This process is further complicated by the necessity to aggregate and analyze vast amounts of influential data. The implementation of decision support systems (DSS) can significantly improve information processing efficiency during the preliminary selection phase. By automating aspects of data analysis and knowledge acquisition, these systems reduce the need for manual human involvement, thereby optimizing the overall decision-making process [1]

1.2 State of the art

In professional volleyball, the number of candidates for a single playing position typically does not exceed

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three to five, enabling experienced coaching staff to make selections without formalized tools. However, the implementation of a decision support system (DSS) remains highly relevant for ensuring objective and standardized evaluation.

This is not solely due to the need to automate the selection process itself, but rather to the desire to standardize evaluation criteria, make the decision-making process more transparent, reduce subjectivity, and ensure consistency of approach across different tournament and training contexts. A DSS not only enables the structuring of analytics during a broad preliminary selection (for example, when reviewing potential newcomers), but also serves as a tool for archiving and formalizing expert experience, which is especially valuable for training young coaches, scouts, or sports analysts. Thus, the objective of the system is not to replace the coaching staff, but to provide flexible, transparent, and reproducible support for decision-making in a dynamic competitive environment.

In modern sports, DSS is extensively used, particularly for player selection. Specifically, the authors of paper [2] conducted a systematic literature review examining various decision-making models and methods for selecting football players using multi-criteria decision making (MCDM) and machine learning (ML).

The selection of a football player involves various performance criteria consisting of technical, physical, mental, and behavioral qualities identified through big data technologies. Based on the results of the review, the creation of a hybrid MCDM model was proposed, taking into account all technical and economic variables to assist decision-makers in selecting the best players. The model uses machine learning algorithms to predict player performance, covering both sporting and financial aspects by analyzing historical data obtained from official club websites. Subsequently, the set of criteria and sub-criteria is evaluated and weighted using an MCDM method such as the analytic hierarchy process (AHP). This weighted evaluation is then applied to rank players for inclusion in squads using the appropriate MCDM methodology. This hybrid model allows for a comprehensive analysis by integrating the strengths of machine learning algorithms for predicting criteria and sub-criteria within decision-making models.

In work [3], the authors propose a decision-making system based on a multi-criteria decision analysis (MCDA) approach, supplemented by sensitivity analysis, to assess the effectiveness of football players. Based on the results of the decisions made, it is possible to adjust the training plan, thereby increasing the player's potential.

Work [4] is devoted to the development and implementation of an expert system based on fuzzy logic, which allows for the parameterization of results of football players and teams, facilitating the assessment of the optimal team composition and predicting match outcomes. To this end, each player was pre-parameterized, taking into account data on their physical condition, skills, psychological state, and specific performance characteristics. Based on these data and the application of various fuzzy logic functions, a series of scores was established for both individual players and teams in order to compare and evaluate match results. In other words, performance parameterization was achieved by combining technical-tactical data (TTD) indicators, psychological readiness, and game situations.

The results of the study [5] showed that various MCDM methods were used to address football-related issues, with many studies focusing on integrating multiple methods to improve decision-making processes. This highlights the growing importance and versatility of MCDM in addressing diverse and evolving challenges in football. Player selection and performance analysis already incorporate these methods to support decision-making, effectively combining MCDM techniques with different fields of knowledge.

The authors of study [6] consider decision-making in sport to involve forecasting and selecting options from a range of possible actions, measures, or management methods. These processes depend on the available information (which is sometimes limited, unreliable, or excessive), the cognitive limitations of the decision-maker (heuristics and biases), the limited time available for decision-making, and the level of risk and reward. Decision support systems are becoming increasingly common in sports contexts, such as schedule optimization, skill assessment and classification, decision evaluation, talent identification, and team selection, or injury risk assessment.

However, there is no specific, formalized structure to help guide the development or evaluation of these systems. Based on a variety of literature, this article proposes a structure for developing a decision support system for specific use in high-performance sport. Three separate criteria are proposed for this purpose: context satisfaction, outcome quality, and process efficiency. The DSS development framework for high-performance sport should help improve both short-term and long-term decision-making in various sporting contexts.

The results of the analysis indicate that DSSs are less common in volleyball, as the majority of research focuses on their application in football. The fundamental differences in the requirements for players in football and volleyball necessitate the adaptation of existing models to the specifics of volleyball, which is one of the key components of the scientific novelty of this study.

The main problem that arises in the process of selecting players is the formation of a player rating based on many criteria. Ranking athletes in a decision support

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system during the pre-selection process is an important step in building an effective team. It allows coaches and managers to evaluate players' abilities based on various criteria and make informed decisions.

For effective selection of athletes, various rating categories can be created, such as an overall rating, a strategic or tactical efficiency rating, etc. Players can also be ranked by specific roles, depending on the sport and the goal.

In team sports, ranking athletes is a complex and time-consuming process because evaluation criteria consist of both qualitative and quantitative characteristics, as well as indirect characteristics related to teams and players.

When selecting players, the coaching staff must take into account many characteristics that directly affect the quality and effectiveness of the team formed. In sports, the ranking is also influenced by the fact that athletes perform in different roles, and the requirements and method of rating formation differ accordingly. However, since the system must process data on athletes of different roles to form a team, the ranking method must take this into account.

Thus, the process of ranking athletes is a complex task, as it affects the effectiveness of decisions made in decision support systems in the sports industry. In the previous work of the authors [7], a decision support system for the preliminary selection of players was proposed. In this system, the key point is the method of supporting decision-making by the coaching staff in the process of preliminary selection of athletes. The method consists of three main steps: information retrieval according to specified criteria; data analysis; and formation of the recommended list of players. In this paper, the study proposes an in-depth consideration of the stage involving the analysis of retrieved information, which is based on the method of ranking athletes in the process of preliminary selection (Fig. 1).

The problem of evaluating and ranking players is a complex multi-criteria decision-making problem. A comprehensive analytical study conducted by the authors [8] showed that the analytic hierarchy process (AHP) and analytic network process (ANP) methods have been successfully used to evaluate team performance, player selection and ranking, team or club performance ranking, and coach evaluation in many sports industries.

The study found that football is the most popular sport in studies using AHP or ANP methods. Basketball is the second most popular sport, followed by baseball and the Olympic Games in general. Athletics, ice hockey, and tennis were also recognized as important sports to which the AHP or ANP methods were applied. In the literature, AHP is used in many other sports. In addition, the authors found several studies that did not directly relate to a particular sport but were related to the sporting sphere in general.

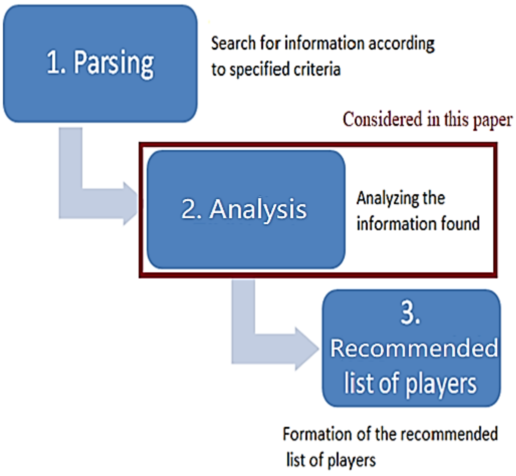

Fig. 1. Steps of the decision support method for the coaching staff in the process of preliminary selection of players [7]

As a result of the literature review, it was concluded that AHP and ANP methods have been successfully used in many sports, such as football, basketball, baseball, athletics, hockey, tennis, American football, badminton, cricket, physical training, archery, golf, judo, recreational sports, relay races, running, swimming, volleyball, and water polo. The methods have been used mainly to measure performance, evaluate and rank a team or player, predict failure, evaluate a coach, evaluate rules in a game, measure technical efficiency, and for sports marketing.

Authors of the work [9] proposed two methods based on data envelopment analysis (DEA) and PageRank to rank college sports coaches. The DEA-based method uses four processes: first, the input factors must pass Kendall's consistency test to ensure that the result is realistic and consistent; second, the data reduction factor represents the consistency of the result; third, the range transfer method standardises the parameters; and fourth, the performance score values for each coach are calculated using the DEA model. The PageRank-based method involves building a network to match coaches whose algorithms are used for ranking. Sensitivity analysis and general analysis methods are used to study and analyse the ranking results for baseball, basketball and football coaches. The PageRank method also takes into account the dynamic and diffusion relationships between coaches. The results are analysed to identify opportunities for improving the method.

Paper [10] discusses the formation of a player rating in e-sports. Competitions in games such as FIFA, Dota2, League of Legends, and Counter-Strike are prestigious tournaments with a global reach and a multi-million dollar budget. On the other hand, a reliable player ranking is a critical issue in both classical and e-sports. The position of each player in the ranking depends on the assessment of their skills and aptitudes. The authors examined the formation of player evaluation and rating using the multi-criteria decision-making method (the method of characteristic objects) COMET, using the example of the popular game Counter-Strike.

In [11], the author examines the assessment of volleyball players' competitive performance using fuzzy integrated assessment. The author proposes to combine fuzzy complex evaluation and the process of analytical hierarchy to build a system for assessing the competitiveness of volleyball players based on the analysis of competitive activity.

The authors of [12] considered the use of the Haddon matrix to determine a strategy for preventing acute sports injuries.

The authors of [13] in their study focus on the widely used technique of ordering preferences by similarity to the ideal solution (TOPSIS), which is used to evaluate the base set of players in the National Hockey League (NHL) in the 2018/2019 season. It is used in conjunction with a number of objective indicator weighting methods to identify differences in indicator use. The indicator weighting method has a major impact on the results obtained and the differences between them, and also supports internal relationships within the ranked set of players. Of the methods reviewed, the authors prefer the average weighting method and recommend that input indicators be considered equivalent when evaluating athletes.

Many multi-criteria decision-making techniques have been developed. The analytic hierarchical process (AHP) technique is a typical multi-criteria decision-making technique that can have advanced knowledge and experience [14, 15].

As an extension of AHP, the fuzzy AHP technique was developed using fuzzy set theory [16, 17].

The technique of ordering by similarity to the ideal solution (TOPSIS) assumes that the best alternative is the alternative closest to the positive ideal solution and furthest from the negative ideal solution [18].

1.3. Objective and structure

Therefore, after conducting the analysis, it can be concluded that in modern sports, decision-making regarding player selection is a complex multi-criteria process that takes into account both objective indicators of an athlete's performance and subjective assessments by the coaching staff. Despite the development of quantitative analysis methods, in practice, the selection of athletes remains largely the prerogative of the coach's expert opinion, due to the limited size of the sample of candidates (usually 3-5 players per position), as well as the need to take into account playing specialisation (position), physical condition, compatibility in relationships and other contextual factors.

The problem is complicated by the fact that the term 'selection' is ambiguous. It can refer to both the formation of the team for the next match and the selection of players for the season or the national team. Each of these scenarios has different goals, criteria, and time horizons, which, in turn, affects the content of performance metrics and the significance of weighting coefficients. In volleyball, where the roles of players differ significantly in terms of function, comparisons should not be made between all athletes, but only between representatives of the same position. Universal ranking of the entire team without taking into account roles or connections (for example, the connection between a setter and an attacker) makes no practical sense and contradicts the structure of team play.

Therefore, the development of a method for ranking volleyball players within a single position is a relevant task. This study addresses this need by incorporating selection context specifics, such as goals, time frames, and candidate composition, into a decision support system designed to complement expert coaching assessments.

To achieve this goal, it is necessary to solve the following tasks:

1) features of the preliminary selection process for volleyball players, taking into account their functional role (position), limited selection of candidates, and the context of decision-making;

2) systematise player performance criteria based on tactical and technical actions (TTA) and other relevant metrics, taking into account the opinions of experts (coaches);

3) justify the approach to constructing weighting coefficients and a generalised rating indicator for players of the same position;

4) develop a method for ranking athletes that ensures adaptability to different selection goals (for a match, for a season, for a national team, etc.).

The main objectives and stages of this study are as follows:

– stage 1: Research and analysis of existing evaluation and ranking methods, identification of their advantages and disadvantages, and setting the task. (Section 1);

– stage 2: Materials and research methods. Features of the preliminary selection process for volleyball players, taking into account their positions (section 2.1). Determination of metrics, parameters and types of information for ranking athletes (section 2.2). Development of a method for ranking athletes (section 2.3);

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– stage 3: Case study, results and discussion: An example of applying the athlete ranking method. (Section 3);

– stage 4: Summarising the results of the study and outlining further directions of development in the field of applied information systems. (Section 4).

2. Materials and methods of research

2.1. Features of the preliminary selection process for volleyball players, taking into account their positions

In volleyball, players are categorized into clearly defined roles, including middle blockers, outside hitters, opposite hitters, setters, and liberos. Each role is characterized by a specific set of technical and tactical actions (TTAs).

In practical contexts, such as match preparation, a coach typically manages only 3 or 4 viable alternatives for each position. When forming a roster for a season, the number of candidates per position rarely exceeds five, and this number may decrease further due to injuries or regulatory restrictions.

Such a small sample size precludes the direct application of classical statistical or machine learning methods in their pure form. Consequently, hybrid approaches are required to integrate expert coaching knowledge with tools for formalizing and visualizing the selection process.

Decision-making must account for the specific context of player selection, as each scenario imposes distinct requirements on the evaluation criteria:

– selection for a high-profile match, where the criterion is maximum reliability;

– selection for an exhibition match, where this criterion can be used to test promising young players;

– selection for training camps, where the criterion of testing interaction is checked;

– selection for a tournament with an intensive schedule, where the criterion of assessing functional reserve is applied;

– selection for the starting line-up, where the criterion of checking readiness to perform a specific tactical role is used.

Therefore, the ranking method must be context-sensitive, allowing for the flexible definition of criteria and weighting coefficients for each situation.

Based on the above, it can be concluded that the development of an athlete rating system should be based on a role-oriented approach characterized by adaptability to the selection context, suitability for small sample sizes, and the integration of expert coaching opinions as a vital component of the final decision.

2.2. Player performance criteria based on tactical and technical actions (TTA)

To ensure objective athlete selection, it is necessary to establish a structured list of metrics that reflect the effectiveness of a volleyball player within their functional role. These metrics form a generalized rating indicator for use within the decision support system.

Sources for establishing these metrics are categorized into two groups: expert and objective. Expert sources include interviews with coaches, analytical documentation from coaching staff, and methodological recommendations from sports federations. Objective sources encompass game statistics (TTA) from official protocols, video analysis with subsequent action coding, and scouting systems.

Given that the definition of metrics is a fundamental stage of the ranking process, the following section examines the procedure for identifying key metrics.

Once identified, these metrics are incorporated into a ranking system that accounts for their relative importance and relevance to each player's role.

Generally, the structure of such a system depends on the specific sport or objective. For the purpose of ranking volleyball players, two groups of parameters are presented, each analyzed using distinct methodologies (Table 1).

Table 1

Parameters

Parameters (1)	Parameters (2)
Parameters of physical development	Technical actions
Level of physical fitness	Tactical actions
Results of competitive activities	Level of special training
General characteristics	Psychological indicators

In general, the rating of a certain player is represented by the formula1:

$$R = (M_1 * W_1) + (M_2 * W_2) + ... + (M_n * W_n)\,, \quad (1)$$

where $M_1 \ldots M_n$ is pre-defined metrics;

$W_1 \ldots W_n$ is appropriate weightings.

2.3. Method of ranking athletes

Elements of artificial intelligence are extensively utilized in the development of sports-related information systems.

For instance, study [19] addresses the inefficiencies within the sports service supply chain resulting from the non-systematic management of stakeholders. The study employs a fuzzy integrated assessment algorithm and artificial intelligence to evaluate and manage risks associated with sports service provision. This algorithm establishes a comprehensive set of factors for risk assessment in the sports service sector. Artificial intelligence serves as a data analytics platform for the integrated risk management of illegal activities in sports. This platform implements logical hierarchical relationships between indicators and rules, standardizes services and regulations, and enables unified monitoring and trend analysis.

Research [20] proposes the use of fuzzy decision support systems to maximize the effectiveness of training programs and enhance individual performance. A strategy titled the Fitness Mamdani Decision System is presented to assist athletes in decision-making to prevent fitness-related injuries. Initially, the system utilizes intuitive fuzzy numbers and fuzzy logic to provide an adaptive framework for improving training program effectiveness. The system accounts for critical factors such as the athlete's mood, fitness level, sleep quality, and stress levels. Mamdani's fuzzy inference system generates rules through the analysis of these core elements. Decision-making for metrics such as adaptability, training load capacity, and program effectiveness is guided by established fuzzy rules.

Study [21] proposes the application of artificial neural networks to predict sports training loads and enhance athletic performance. The study utilizes the artificial fish swarm algorithm (AFSA) for the modeling and prediction of training loads. Initial weights and thresholds for the artificial neural network are optimized via AFSA. The final prediction results are obtained by combining the optimized ANN and load characteristics with a prediction equation. This model is integrated into a sports training analysis system to facilitate load prediction. Experimental results demonstrate that the proposed methods effectively enhance the accuracy of load prediction and improve overall athletic competitiveness.

Work [22] proposes a ranking system that considers both win-loss records and specific performance indicators, alongside external attributes such as the toss and home-field advantage. Consequently, features are developed to assess team superiority in specific areas compared to competitors. These features are integrated to establish a consistency index for ranking cricket teams. The methodology was validated against International Cricket Council rankings using the Spearman rank correlation coefficient across all three cricket formats (Test, ODI, and T20). The results demonstrate that the proposed methods provide superior outcomes for ranking cricket teams.

Study [23] evaluates the integration of decision support systems with time-series analysis in professional basketball. The authors propose a changepoint-based methodology to quantify Most Demanding Scenarios (MDS) by analyzing high-resolution optical tracking data. Unlike traditional fixed-window methods, this approach identifies peak physical demands based on the actual duration of intensive gameplay. The results demonstrate that such automated systems significantly enhance the ecological validity of performance metrics, providing a robust foundation for tactical substitutions and individualized training load optimization.

Research [24] focuses on the implementation of a DSS to enhance the assessment of movement proficiency by correlating subjective expert grading with objective biomechanical indicators. The study utilizes predictive modeling to demonstrate that automated systems can accurately replicate expert evaluations during complex movement tasks, such as the single-leg squat. By identifying a minimal set of key indicators that drive expert decisions, the proposed framework facilitates standardized and accessible athlete assessment. This methodology underscores the potential for integrating expert heuristic knowledge into formalized algorithmic systems, ensuring greater consistency in talent identification and performance monitoring.

Study [25] proposes a proof-of-concept predictive modeling framework designed to identify elite athletes in team sports. The authors evaluate the performance of several machine learning algorithms, specifically XGBoost, Random Forest, and LightGBM, to classify players based on their performance metrics. The research emphasizes the importance of balancing precision and recall in the scouting process to ensure that high-potential candidates are not overlooked. By automating the screening and shortlisting stages, the proposed system provides a data-driven approach to athlete selection, significantly reducing the subjectivity inherent in traditional scouting methods. This work validates the utility of ensemble learning methods in sports talent identification and strategic roster management.

Study [26] proposes a Decision Tree-based classification model to evaluate athlete potential in athletics. Utilizing the CRISP-DM framework and RapidMiner software, the authors analyzed a dataset of 450 athletes to automate the identification of high-potential individuals. The resulting model achieved a classification accuracy of 92.22%, identifying ranking as the primary determinant for separating athletes into distinct potential categories. By replacing subjective observational assessments with objective, rule-based data analysis, this system enhances the transparency and consistency of the talent identification process in track and field.

Thus, the existing body of research confirms that the use of artificial intelligence to enhance decision-making in sports is scientifically sound. However, while

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recent advancements show significant success in sports such as basketball and athletics, these methodologies are often difficult to adapt to volleyball due to its high role-specificity and the limited number of candidates per position. Consequently, there is a clear need to develop a hybrid approach that integrates expert heuristic knowledge with comprehensive performance data to address this specific gap in the field.

The proposed ranking method within the DSS consists of two integrated components designed to process the parameter groups defined in Table 1. Due to the structural complexity of these indicators, which include both quantitative metrics and qualitative expert assessments, a hybrid computational approach is employed. Specifically, fuzzy logic (IF-THEN rules) is applied to the first group to handle qualitative uncertainty, while artificial neural networks (ANN) are utilized to process the second group of parameters.

To identify hidden non-linear dependencies between the technical and tactical performance indicators of players, an artificial neural network (ANN) module has been implemented within the system. The proposed architecture, illustrated in Fig. 2, is based on the multilayer perceptron principle and is optimized for processing the multidimensional characteristics of athletes' technical and tactical preparedness.

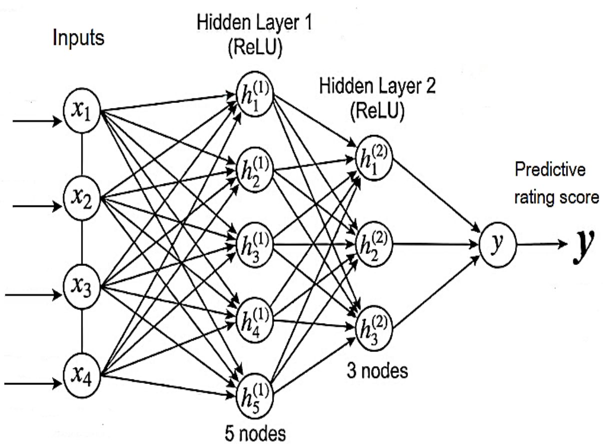

Fig. 2. Structure of the proposed artificial neural network for multidimensional analysis of player performance

The input layer comprises four neurons representing normalized parameters for technical actions, tactical actions, special training, and psychological indicators. A two-layer hidden structure has been implemented, consisting of five nodes in the first layer and three in the second, utilizing the Rectified Linear Unit (ReLU) activation function. The selection of the ReLU function is justified by its high computational efficiency and its capability to mitigate the vanishing gradient problem, which ensures rapid convergence of the learning algorithm when processing multidimensional datasets. This approach enables the model to accurately capture complex non-linear relationships within technical and tactical performance metrics, providing coaches with an objective analytical basis for ranking prospective players. Furthermore, such a configuration facilitates gradual data distillation and prevents model overfitting when operating with limited sample sizes.

The output layer is represented by a single neuron that generates a predictive potential score based on the analysis of input metrics. The scalability of the architecture allows for the expansion of the input vector with morphofunctional indicators, facilitating the system's adaptation to various team sports. Further model enhancement is directed towards analyzing training dynamics and developing analytical decision-support tools for coaches to assist in the selection and developmental planning of promising players.

In the proposed method, an ANN is utilized as a core component for identifying latent relationships between TTA indicators.

The decision support system (DSS) for volleyball player selection implements a hybrid ranking method that combines a deterministic component, in the form of IF-THEN production rules, with an adaptive model based on an artificial neural network.

This architecture enables the integration of expert heuristic knowledge with automated data-driven learning, ensuring decision explainability and the model's robustness in complex environments.

At the first level, the system performs an initial screening of candidates using a predefined set of logical rules derived from expert assessments by coaches and analysts.

These rules process formalized metrics, such as physical development, fitness levels, and competition history, to identify players who meet the basic functional criteria for a specific position.

At the second level, an ANN module is integrated to perform a multidimensional analysis of the players' numerical characteristics. Due to the ability of neural networks to detect latent non-linear dependencies between variables, the model provides a predictive assessment of a player's overall potential.

This approach proves particularly effective in scenarios where manually formulated rules cannot fully capture the complex interdependencies between variables.

The final output integrates a binary classification (fit/unfit) from the production system with a quantitative rating generated by the neural network.

These results can be mapped to a formalized scale for further ranking or utilized as primary input for final decision-making by the coaching staff.

This structure ensures an optimal balance between interpretability, accuracy, and adaptability within the athlete selection process.

Formula 1 is the basis for determining the rating of an athlete at the beginning of, for example, the training or competition periods. Then, with the value of this rating, the athlete enters the process and his or her rating can either increase or decrease. In the ranking subsystem, you can create different categories of ratings, such as overall rating, strategic efficiency, tactical efficiency, etc. You can also rank players by specific roles, depending on the sport and the goal.

So, based on all of the above, we will formulate a method for ranking athletes. The method is shown schematically in Fig. 3.

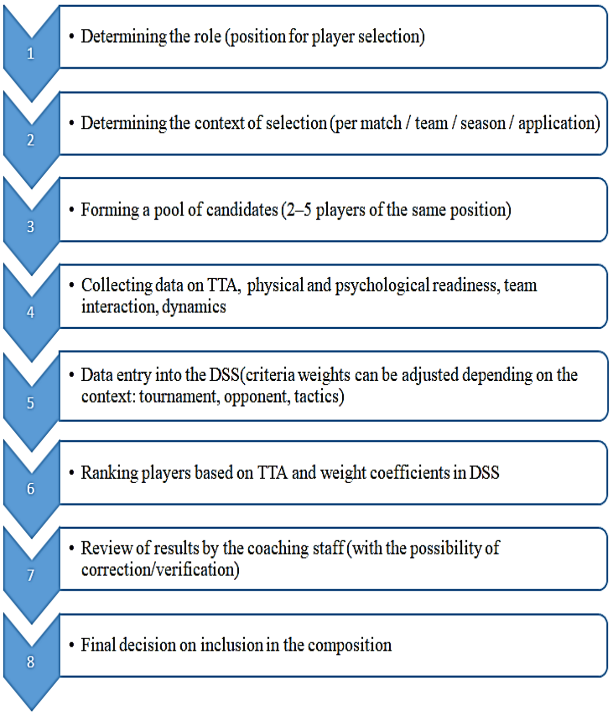

Fig. 3. Schematic representation of the method of ranking athletes in the decision support system in the process of preliminary selection of players

3. Case study, results and discussion

This section presents the operational framework of the athlete ranking method within the decision support system (DSS) for preliminary player selection. The metrics, weighting coefficients, and parameters integral to the proposed method were established based on expert evaluations provided by the coaching staff of the «Podillya» Volleyball Club (Khmelnytskyi). The method utilizes a periodic rating index, denoted as p, with an initial value of p = 0.

This rating is dynamic, meaning the value of p can either increase or decrease based on performance. The governing rules of the proposed method are defined as follows:

1. IF the average speed of the athlete for the last three training sessions increased during the week, THEN p = p+1.

2. IF the athlete has reached a certain indicator in an important competition (for example, made a certain number of effective passes), THEN p = p+1.

3. IF the athlete did not follow the training plan for a certain period of time (for example, missed training two times in a row), THEN p = p - 1.

4. IF the athlete's average physical performance has been falling over the last two weeks, THEN send a notification to the coach to revise the training programme, p = p - 1.

5. IF the athlete's sleep duration has been falling for a long period of time, THEN p = p - 1.

6. IF the athlete has achieved a certain level of performance in training tasks that are specifically selected to improve a particular aspect of the game, THEN p = p+1.

7. IF the athlete has improved in two or more aspects of the game in the last month, THEN p = p+1.

8. IF the striker has played several matches without a goal, THEN p = p - 1.

9. IF the athlete has improved his/her health level (measured by physical and heart rate) in the last month, THEN p = p+1.

10. IF the chosen strategy of the athlete's game has led to a decrease in the number of errors and improved results in competitions, THEN p = p+1.

11. IF the level of motivation of the athlete, determined by his/her activity in training and compliance with coaching recommendations, increases over a long period of time, THEN p = p+1.

12. IF an athlete's level of self-discipline, as measured by their ability to follow training plans and adhere to lifestyle recommendations, declines over a long period of time, THEN p = p - 1.

13. IF the athlete's recovery time from an injury or illness exceeds the average recovery time for his/her sport, THEN p = p - 1.

14. IF the athlete shows steady progress in improving training performance over a period of time, THEN p = p+1.

15. IF the athlete does not follow dietary recommendations or uses harmful substances that may adversely affect his/her physical fitness, THEN p = p - 1.

16. IF the athlete has tried a new game strategy or training programme that has led to an improvement in his/her performance, THEN p = p+1.

17. IF the athlete has won an important competition or achieved a key goal set by the coach, THEN p = p+1.

18. IF the athlete has shown a poor result in training over a certain period, THEN contact the coach or medical

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staff for further investigation of the causes and action, p = p - 1.

19. IF the athlete performs well in training or competition for several consecutive weeks, THEN p = p+1.

20. IF the athlete shows a high level of consistency in the performance of key tasks or skills, THEN p = p+1.

21. IF the athlete increases the frequency and intensity of training according to the coach's recommendations, THEN p = p+1.

22. IF the athlete is exposed to risky activities or dangerous situations during training or competition, THEN p = p – 1.

23. IF the athlete demonstrates excellent teamwork and leadership skills in group training or competition, THEN p = p+1.

24. IF the athlete improves his/her level of fitness or technical skills over a long period of time, THEN p = p+1.

Determining the key performance metrics for volleyball players requires a comprehensive analysis of various multifaceted game-play aspects.

Within the proposed method, the sum of the assigned weighting coefficients must equal 1 to ensure a normalized evaluation of the candidates.

1. Attack:

– success of attacks (accuracy), weighting factor – 0.25;

– number of attacks per game, weighting factor – 0.15.

2. Serve:

– number of aces, weighting factor – 0.10; number of service errors, weighting factor – 0.10.

3. Blocking:

– number of blocks per game, weighting factor – 0.20;

– success of blocks (accuracy), weighting factor – 0.10.

4. Accuracy of receiving serves, weighting factor – 0.10.

Evaluating players. To demonstrate the practical application of the proposed method**,** a sample group of five players was selected for evaluation.

For each athlete, performance scores across all defined metrics were collected and adjusted using the established weighting coefficients.

The results are presented in Table 2.

Calculation of the total score. The rating of each player is calculated as follows.

$$rp = (RA*0.25)+(A*0.15)+(KE*0.1)+ \\ +(WP*0.1)+(B*0.2)+(RB*0.1)+(TP*0.1), \quad (2)$$

Example of rating calculation for Player 1:

$$rp = (8*0.25)+(7*0.15)+(6*0.1)+(3*0.1)+ \\ +(7*0.2)+(8*0.1)+(6*0.1) = 6.75, \quad (3)$$

The rating calculation for all players is presented in Table 3.

Ranking of players. Based on the total score, we can rank the players according to the rating obtained using part 2 of the ranking method.

1. Player 3 – 7.00.
2. Player 5 – 7.00.
3. Player 2 – 6.85.
4. Player 1 – 6.75.
5. Player 4 – 5.80.

Thus, players 3 and 5 have the highest total score in part 2 of the player ranking method and can be considered the most successful according to the selected criteria.

According to part 1 of the ranking method, the players' results were distributed as follows (Table 4).

Table 2

Rating table

	Player1	Player2	Player3	Player4	Player5
Attack success rate (RA)	8	9	7	6	7
Number of attacks (A)	7	6	8	5	7
Number of aces (KE)	6	5	7	4	8
Number of errors in serving (WP)	3	4	2	6	3
Number of blocks (B)	7	6	8	5	7
Block success (RB)	8	7	9	6	8
Accuracy of receiving (TP)	6	7	5	8	6

Table 3

Calculating the score

Players	Calculated score
Player1	6.75
Player2	6.85
Player3	7.00
Player4	5.80
Player5	7.00

Table 4

Calculation of the rating

Players	Counter value
Player1	24
Player2	19
Player3	15
Player4	22
Player5	20

Consequently, the final athlete ranking, derived using the proposed method within the decision support system for preliminary player selection, is presented Table 5.

Table 5

Overall player rating

Players	Total score
Player1	30.75
Player2	25.85
Player3	23.00
Player4	27.80
Player5	27.00

The results of the player ranking:

1. Player 1 – 30.75.
2. Player 4 – 27.80.
3. Player 5 – 27.00.
4. Player 2 – 25.85.
5. Player 3 – 23.00.

Based on the results, the coaching staff can make decisions about player selection. It should be noted that it is better to form a rating based on the players' roles, as different parameters are important for different players.

Taking into account the large amount and heterogeneity of data that must be processed for decision-making by the coaching staff in the preliminary selection of players, the authors in paper [2] proposed a decision support system for the preliminary selection of players.

The place of the developed method of ranking players in the structure of the proposed system is shown in Fig. 4.

4. Conclusions

Currently, the quality of decision-making in various industries is crucial for improving operational efficiency. This is a fundamental aspect when developing decision support systems. In the sports industry, where vast amounts of diverse data and parameters must be collected and analyzed by coaching staff and sports managers, such systems help automate this routine tasks. Such systems also significantly increase the efficiency of information processing during the preliminary selection of athletes. The process of preliminary selection is an important stage in forming national teams for championships at various levels, as well as the primary roster for club competitions. In the preliminary selection process, it is necessary to process vast amounts of diverse data and make informed decisions, since selection accuracy directly affects the quality of the resulting team.

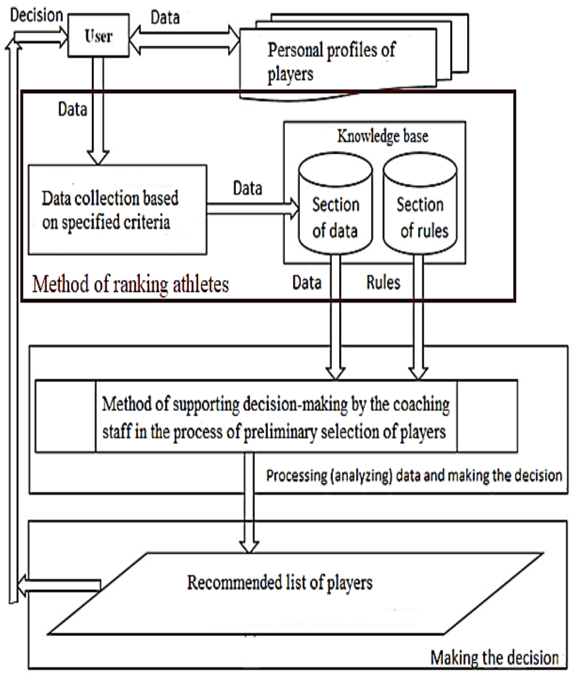

Fig. 4. Structure of the decision support system for the coaching staff in the process of preliminary selection of players [2]

The article proposes an athlete ranking method which, based on specific metrics, a set of rules, and weighting coefficients, enables the formation of a player rating within a decision support system during the preliminary selection process. Unlike existing approaches, this method consists of two parts to account for two distinct groups of parameters. Since these parameters are complex in structure, encompassing quantitative and qualitative, crisp and fuzzy, as well as formalized and informal values, it is proposed to utilize fuzzy logic in the form of IF-THEN rules for the first group and artificial neural networks (ANN) for the second. The first group of parameters is described by these rules and includes information regarding the level of physical development, fitness, competitive results, and

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general characteristics. To account for the second group of parameters, an artificial neural network is employed, as this group includes metrics such as technical and tactical actions, specialized training levels, and psychological indicators.

The proposed athlete ranking method within the DSS is innovative because it combines a structured system of tactical and technical action (TTA) indicators with role-specific criteria weighting obtained through expert consensus. This integration allows the model to be adapted to the specific selection context. The scientific novelty also includes the integration of a neural network component as a means of identifying latent dependencies between performance indicators dynamically. This approach has not previously been applied to short-term selection tasks in volleyball.

Experimental results demonstrate the effectiveness of the proposed method.

Further research will focus on developing adaptive player models and optimizing the selection process to enhance the efficiency of decision-making within the DSS.

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All the authors have read and agreed to the published version of this manuscript.

Conflict of Interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, author ship or otherwise, that could affect the research and its results presented in this paper.

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Data Availability

The manuscript has no associated data.

Use of Artificial Intelligence

The authors confirm that they did not use artificial intelligence methods while creating the presented work.

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МЕТОД РАНЖУВАННЯ СПОРТСМЕНІВ У СИСТЕМІ ПІДТРИМКИ ПРИЙНЯТТЯ РІШЕНЬ У ПРОЦЕСІ ПОПЕРЕДНЬОГО ВІДБОРУ ГРАВЦІВ

Є. Г. Гнатчук, Т. О. Говорущенко, А. Я. Гнатчук

Темою статті є метод ранжування спортсменів у системі підтримки прийняття рішень у процесі попереднього відбору гравців. **Мета статті** – розробити метод ранжування гравців у системі підтримки прийняття рішень, який дозволяє враховувати всі види інформації, доступної тренерському штабу, і приймати

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обґрунтоване рішення, оскільки правильність відбору безпосередньо впливає на якість сформованої команди. **Завдання дослідження**: дослідити типи інформації, що використовуються в процесі ранжування спортсменів, вибрати відповідні методи представлення та обробки цієї інформації; розробити метод, який на основі певних метрик, набору правил, вагових коефіцієнтів та апарату штучної нейронної мережі дозволяє сформувати рейтинг гравців у системі підтримки прийняття рішень у процесі попереднього відбору гравців; провести експеримент для підтвердження ефективності методу. **Результати дослідження**: у статті запропоновано метод ранжування спортсменів, який є гібридним підходом, що інтегрує детермінований компонент у вигляді системи виробничих правил IF-THEN та адаптивну модель на основі штучної нейронної мережі. Така структура дозволяє поєднувати експертні знання та автоматизоване навчання на основі даних, забезпечуючи як пояснюваність рішень, так і здатність моделі генерувати рішення в складних умовах. На першому рівні система ранжує кандидатів за допомогою заздалегідь визначеного набору логічних правил, сформульованих на основі експертних оцінок тренерів та аналітиків. Ці правила оперують формалізованими метриками (зокрема, параметрами фізичного розвитку, рівнем фізичної підготовки, результатами змагань та загальними характеристиками), що дозволяє провести початкове ранжування та відбір гравців, які не відповідають основним критеріям функціональної придатності для даної позиції. На другому рівні обробки підключається модуль ANN, який виконує багатовимірний аналіз числових характеристик гравців. Завдяки здатності нейронних мереж виявляти приховані, потенційно нелінійні залежності між тактичними та технічними діями, антропометричними показниками та іншими параметрами, модель робить прогнозну оцінку загального потенціалу гравця. Цей підхід є особливо ефективним у випадках, коли сформульовані вручну правила не охоплюють складні взаємозв'язки між змінними. Комбінований результат складається з бінарного рішення (відповідає/не відповідає) на основі виробничої частини системи та рейтингу, отриманого на виході нейронної мережі. Ці значення можуть бути об'єднані в формалізовану шкалу для подальшого ранжування кандидатів або використані як вхідні дані для остаточних рішень тренерського штабу. Така структура дозволяє досягти балансу між інтерпретованістю, точністю та адаптивністю в процесі відбору волейболістів. **Висновки**: Наукова новизна представленого методу ранжування спортсменів полягає в тому, що метод поєднує структуровану систему тактичних і технічних показників із специфічною для ролі вагою критеріїв, отриманою за допомогою експертної згоди, що дозволяє адаптувати модель до контексту конкретного відбору. Наукова новизна також полягає у включенні компонента нейронної мережі як додаткового засобу виявлення прихованих залежностей між показниками ефективності гравців у динаміці, що раніше не використовувалося в завданнях короткострокового відбору у волейболі.

Ключові слова: система підтримки прийняття рішень; прийняття рішень; критерії прийняття рішень; метод ранжування; правила; штучні нейронні мережі; попередній відбір гравців.

Гнатчук Єлизавета Геннадіївна – д-р техн. наук, проф., проф. каф. комп'ютерної інженерії та інформаційних систем, Хмельницький національний університет, Хмельницький, Україна.

Говорущенко Тетяна Олександрівна – д-р техн. наук, проф., декан факультету інформаційних технологій, Хмельницький національний університет, Хмельницький, Україна.

Гнатчук Аліна Ярославівна – асп. каф. комп'ютерної інженерії та інформаційних систем, Хмельницький національний університет, Хмельницький, Україна.

Yelyzaveta Hnatchuk – Doctor of Technical Sciences, Professor, Professor at the Department of Computer Engineering and Information Systems, Khmelnytskyi National University (KhNU), Khmelnytskyi, Ukraine,
e-mail: liza_veta@ukr.net, ORCID: 0000-0003-2989-3183, Scopus Author ID: 57211621395.

Tetiana Hovorushchenko – Doctor of Technical Sciences, Professor, Dean of the Faculty of Information Technology, Khmelnytskyi National University (KhNU), Khmelnytskyi, Ukraine,
e-mail: tat_yana@ukr.net, ORCID: 0000-0002-7942-1857, Scopus Author ID: 54420153900.

Alina Hnatchuk – PhD Student of the Computer Engineering and Information System Department, Khmelnytskyi National University (KhNU), Khmelnytskyi, Ukraine,
e-mail: alinahnatchuk@ukr.net, ORCID: 0000-0003-0155-9255, Scopus Author ID: 57223109055.