Enhanced Adaptive Rough Decision Optimization for Athletic Training Periodization: A Computational Framework

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Choosing the most effective periodization strategy in athletic training is essential for enhancing performance and reducing the likelihood of overtraining. This paper proposes a novel method, the Enhanced Adaptive Rough Decision Optimization (EARDO) Algorithm, for evaluating and ranking periodization strategies. The EARDO algorithm is designed to accommodate the dynamic, multifactorial nature of athletic training, where training load impact depends on factors such as daily variability, recovery, individual responses, and intensity. The algorithm integrates adaptive rough set theory to handle uncertainty and captures the trade-offs in performance gains and injury risks. The effectiveness of the EARDO approach was evaluated through computational experiments on three periodization strategies—linear, undulating, and block. The results showed that EARDO could accurately determine the optimal training load for each athlete (98.75%), assess overtraining risk (98.5%), and identify overtraining periods (98.35%). Comparisons with existing fuzzy logic and rough set methods revealed a substantial improvement in accuracy (6-8% higher) for selecting optimal periodization strategies and predicting overtraining and injury risks. These findings suggest that the EARDO algorithm offers a more precise, flexible, and adaptable framework for optimizing athletic training.

Povzetek: Razvit je nov pristop za optimizacijo periodizacije v atletskem treningu, imenovan Enhanced Adaptive Rough Decision Optimization (EARDO), ki uporablja adaptivne algoritme za obvladovanje dinamičnih sprememb v intenzivnosti treninga in okrevanju ter omogoča boljše odločitve za preprečevanje pretreniranosti in izboljšanje uspešnosti.

1 Introduction

Periodization is a technique used in different sports activities. The primary purpose of this strategy in athlete training is to maximize the performance of athletes by minimizing the risks of illness or any other mental health disturbance [19]. Of the distinct types, linear, undulating, and block periodization are the most used in sports science [?]. However, these strategies are not unproblematic because many factors play a role, among which are the level of athletic fitness, the goals of training, and the periods of athletic rest [22]. Therefore, identifying the optimal periodization strategy is a twofold process considering the positive impact on performance and the adverse effects on health [11]. For this reason, we also require more advanced computerized models to select the most applicable periodization techniques based on the relevant performance measures to make more effective decisions [3]. Over the last few decades, approaches like fuzzy logic and rough set theory were employed to address different issues related to athletic training models, particularly on the issue of multiple criteria decision-making [13]. Several studies show that these methods can assist in managing the fuzziness and imprecision associated with training programs. For instance, fuzzy logic can approximate how human decision-making occurs when such decision-making is done without sufficient input data sets, and the rough sets can be used to solve problems with incomplete data [1]. However, these models fail to capture the dynamism and change over time of athletic performance, where every training decision is mutually beneficial and detrimental [17]. The problems with the methods currently used to model training regimens mean that a new, more flexible approach is needed. Therefore, there is an increasing demand for computational frameworks that can effectively analyze and predict training outcomes while integrating the athlete's evolving performance metrics. Such tools should also incorporate the potential for feedback loops, enabling real-time adjustments in training protocols.

Conventional periodization models (linear, undulating and block) show inadequate results in athletic preparation because they cannot properly address the dynamic nature of

Table 1: Overview of latest technologies and methods in athletic training periodization

Approach/Technology	Key Features	Limitations
Fuzzy Logic	Handles uncertainty in decision-making	Limited ability to adapt to real-time changes in athlete performance
Rough Set Theory	Deals with incomplete or uncertain data	Lacks adaptability and dynamic decision-making in real-time training conditions
Machine Learning Algorithms	Learns from data, making decisions based on past performance	Requires large amounts of data and computational resources
Linear Periodization	Fixed training intensity and progression over time	Does not account for fluctuations in athlete performance or recovery
Undulating Periodization	Varying intensity based on the athlete's needs	Less effective for real-time adjustments and individualized training
Block Periodization	Focuses on intensive training blocks for specific goals	Does not adjust to changing athlete conditions during the training process
EARDO (Proposed)	Real-time adjustments based on athlete's performance and recovery	Requires real-time data and may be computationally intensive

training across multiple variables. The traditional strategies primarily deal with performance enhancement and injury prevention without acknowledging the day-by-day variations in training volume and athletic rehabilitation patterns. EARDO serves as an innovative solution because it applies adaptive decision systems that track performance and recovery variables to enable immediate training load adjustments. The EARDO system provides adaptable protocols through which it modifies training operations based on dynamic athlete states, thereby achieving better outcomes without compromising safety. The key benefit of EARDO as a progress in athletic training lies in its daily adaptability to training intensity and recovery processes and individual performance responses. Table 1 provides the overview of latest technologies and methods in athletic training periodization.

1.1 Background on periodization in athletic training

Athletic periodization has been employed for many years as a powerful tool to help athletes arrange their training to work towards their highest potential and achieve the desired recovery time. Initially designed for Olympic-type sports that require preparation over a relatively long period, periodization techniques have been modified to suit the requirements of different categories of athletics [20]. The idea of periodization is to split a training program into various stages, where every stage has other aims, such as building stamina, increasing muscle mass, or working on one's speed [14]. These phases are planned so that athletes are at their best during critical times of the competition year.

The problem with periodization so far is the understanding that these phases must be applied to the sportsman based on their fitness, training requirements, and recovery ability, and it is still precious as it offers a precise sequence of training phases [?]. Several fundamental models of periodization, such as linear, undulating, and block periodization, tell us a bit about how things are done. But they do not always permit us to explain how people might react in varying ways to different training masses [22]. As a result, it has been discovered that traditional periodization models may not be ideal for every athlete, especially not in dynamic and high-impact sports where changes in training can make a significant difference in the final results. To manage these issues, the contemporary studies have developed decision-support models with account data-driven solutions to periodization decision-making. However, despite these developments, numerous models cannot handle athletic performance's natural variability and stochastic elements. For these reasons, this paper advocates for an enhanced, flexible periodization system that will restore the efficient computation of optimum periodization on each athlete, which inspired the development of the Enhanced Adaptive Rough Decision Optimisation (EARDO) algorithm in this paper.

1.2 Limitations of previous studies

Despite improvements in decision-making techniques for athletic training, there remain significant concerns. In particular, most existing studies focus solely on fuzzy or rough set theory without incorporating fully developed adaptive algorithms that can adjust training based on real-time changes in an athlete's needs. This limitation results in models that are not flexible enough to address the dynamic nature of athletic training. Traditional models, by not considering daily variations in performance, recovery, and intensity, may fail to optimize training loads effectively and could lead to less-than-ideal conditions for the athlete. Furthermore, many studies lack a systematic framework for balancing performance enhancement with safe recovery, which is crucial for athletic trainers [5]. The current models also do not account for individualized periodization strategies, which are essential for tailoring training programs to the specific needs of individual athletes. These limitations highlight the need for a more adaptable model that can address the complex, multifactorial elements of athletic training, such as variable intensity, recovery, and individualized needs, which are essential for maximizing performance and minimizing injury risks.

1.3 Motivations and novel contributions

This study introduces the Enhanced Adaptive Rough Decision Optimization (EARDO) Algorithm, a model specifically designed to address these limitations in athletic training periodization. The contributions of this study are as follows:

- Development of the EARDO algorithm, integrating adaptive rough set theory to handle better the dynamic and uncertain nature of athletic training decisions.
- An innovative approach to customizing periodization strategies for individual athletes, taking into account unique performance profiles and recovery requirements.
- Demonstrated improvement in accuracy, sensitivity, and recall rates over traditional methods for selecting optimal periodization strategies and predicting overtraining risks.
- Creation of a flexible decision-making tool that balances multiple, often conflicting, criteria, such as maximizing performance while minimizing injury risks, thus providing coaches and sports scientists with a robust framework for training optimization.

This paper is well organized by looking at the proposed EARDO method and how it can be used in athletic training in the following sections. Section 2 discusses the problems with previous approaches to choosing a periodization strategy. Section 3 outlines the methodology behind the EARDO algorithm, detailing its framework and application to real-world training scenarios. Section 4 evaluates the effectiveness of the proposed method through empirical analysis, highlighting its superiority over traditional models. Section 5 discusses the interpretations of the results and the comparison with other approaches, followed by the limitations and future works. Finally, Section 6 concludes the whole study.

2 Related work

The field of decision-making frameworks has seen significant advancements in recent years, particularly in handling imprecise and multifaceted data in various domains. These innovations have not only enhanced theoretical understanding but also demonstrated practical applications in areas such as sports analytics, health management, and material selection. This section highlights notable contributions in this area, emphasizing their relevance to decision-making and optimization challenges.

Khizar et al. [8] came up with the group-based generalized interval-valued q-rung ortho-pair fuzzy soft set (GGIVq-ROFSS) model for making decisions based on multiple competing criteria when the decision information is not entirely accurate. They described how the selected rating system is less arbitrary using intervals than grades through the GGIVq-ROFSS framework. This was used in sports decision-making to analyze the performances of football teams, distinguish their positions on the field, and assess players' abilities. The authors proposed two new types of aggregation operators, namely the GGIVq-ROFSWA and GGIVq-ROFSWG, which smooth sub-alternatives in the decision-making process. Their method was used to evaluate city performances based on the achievements of athletes in various sports clubs, proving the proposed method's capacity for improved decision-making in sports.

Qiyas et al. [15] introduced Confidence Levels Bipolar Complex Fuzzy Set (CLBCFS) to manage imprecise and intricate information in decision-making issues. They developed theories for confidence levels, bipolar, and complex fuzzy sets, forming the basis for CLBCFS. Regarding bipolar complex fuzzy collections, the study elaborated operational laws and presented bipolar complex fuzzy averaging and geometric operators. The authors examined significant results connected with these operators and described their essential characteristics. Further, they applied the CLBCFS model to multiple-attribute decision-making, using examples to demonstrate its efficiency. Their work has enhanced BD's capacity for decision-making in complex and ambiguous conditions. The authors also compared the method with previous solutions, confirming the CLBCFS model's efficiency, and provided geometrical illustrations [12].

Hu et al. [10] developed an integrated intelligent decision for assessing the physical health of college students using fuzzy number intuitionistic information. They sought an academic and pragmatic index system to evaluate students' physical health status systematically. The work generalized the GHM and GWHM operators as FNIFGHM and FNIFGWHM operators with fuzzy and intuitionistic fuzzy numbers. These operators were applied to multiple attribute decision-making (MADM) problems related to the physical health assessment of college students. A case study supported the approaches, evidencing a more accurate and scientific evaluation. The study emphasized the importance of correctly evaluating students' health to improve physical education and ensure students attain effective exercise regimens.

Fahmi et al. [6] proposed conceptualizing linguistic interval-valued bipolar neutrosophic fuzzy numbers and their relevant operational laws. They have defined the score and accuracy functions and derived six new aggregation operators, namely, LGIVBNEFWA, LGIVBNE-

FOWA, LGIVBNEFHWA, LGIVBNEFWG, LGIVBNE-FOWG, and LGIVBNEFHWG. Some of these operators were presented with essential theorems, and various cases were discussed and analyzed. Further, they presented two new methods based on these developed aggregation and geometric operators. Different numerical examples provided evidence of the applicability of the techniques for improving decision-making efficiency in the context of the proposed and existing methods [23].

Aamir et al. [16] proposed a fuzzy-TOPSIS MCDM method for material selection, incorporating SHE risk evaluation. They emphasized integrating SHE aspects into the material selection process for sustainable design and manufacturing. The authors introduced a fuzzy TOPSIS technique to evaluate SHE-related risks and rank material alternatives, providing a practical way to select, evaluate, and prioritize materials based on design requirements and decision-maker weights. The study avoided complex structures and black-box algorithms, opting for straightforward solutions addressing qualitative estimation and quantitative measurement uncertainties. The proposed model was used in sample selection during group decision-making of upper limb prostheses. An algorithm [2] explained the method's design, and comparisons of the case with other present-fuzzy theories, including mF soft expert sets and fuzzy soft expert sets, spoke to the applicability of this approach to the advancement of decision-making. A real-life case was also highlighted to determine the best prosthesis sample of the nine choices available in the natural business environment using the IVFSE model [24].

Collectively, these studies underscore the growing importance of advanced decision-making frameworks in addressing complex, multi-criteria problems across diverse domains. The continuous evolution of these models highlights the need for future research to develop even more dynamic, adaptive, and precise methodologies to tackle emerging challenges in decision-making. Table 2 compares the reviewed approaches and gaps in SOTA.

3 Methodology

The Enhanced Adaptive Rough Decision Optimization (EARDO) algorithm for choosing effective periodization for athletes' training has shown excellent credibility. This phase outlines how the model has been adopted to compare the various types and forms of periodization and the method related to criteria selection. Due to the multifaceted specificity of the athletic training field, the EARDO algorithm effectively solves the information uncertainty and athleticism course training professionalism of the field by giving exact instructions to reduce risk and maximize positive results.

3.1 Workflow of the methodology

The decision-making process follows a structured workflow, as depicted in **Figure 1**. The workflow begins by defining the alternatives (periodization strategies) and criteria (e.g., strength, endurance, recovery, injury risk). These alternatives and criteria are selected based on expert inputs, which are typically drawn from domain-specific knowledge, such as inputs from sports scientists, coaches, and training specialists. After defining the alternatives and criteria, data collection follows, where performance, recovery, and injury metrics are gathered. The collected data is then used to evaluate the alternatives and assess how well each strategy meets the set criteria.

The next step in the workflow is to apply the EARDO algorithm, which uses the collected data to compute scores for each alternative based on the predefined criteria. The final selection is made by ranking the alternatives according to these scores, which are adjusted dynamically by the algorithm during the evaluation process.

3.2 Framework of the EARDO model

The EARDO model integrates adaptive rough set theory to accommodate the performance benefits and potential risks associated with training decisions. This framework is designed to address the inherent complexity and uncertainty in athletic training, providing a robust mechanism to evaluate diverse periodization strategies under varying conditions. By leveraging adaptive rough set principles, the model ensures that both quantitative performance metrics and qualitative risk factors are systematically accounted for in the decision-making process.

The model begins by defining a set of alternatives A_i (such as different periodization strategies) and criteria C_j (such as strength, endurance, recovery time, and injury risk) that are critical for athletic performance. These alternatives and criteria are selected based on expert inputs, ensuring relevance and applicability across diverse athletic contexts.

For each alternative A_i, the evaluation against each criterion C_j is expressed as an adaptive score that captures both positive and negative impacts, ensuring a balanced assessment. The model incorporates these scores into an aggregated evaluation metric to facilitate direct comparisons among alternatives. The overall score for each alternative is computed using the formula:

$$S_i = \sum_{j=1}^{n} w_j \times V_{ij} \tag{1}$$

Where:

- S_i represents the overall score for the i-th alternative, providing a single performance indicator for decision-making.
- w_j is the weight assigned to the j-th criterion, reflecting its relative importance as determined by domain experts.
- V_{ij} is the value derived from adaptive rough decision-making, capturing both performance benefits and risks for criterion C_j under alternative A_i.

Table 2: Comparison of reviewed approaches and gaps in SOTA

Author(s) and Citation	Key Features	Accuracy	Adaptability to Context	Gaps Addressed by EARDO
Khizar et al. [8]	Handles vague and imprecise data but ignores dual effects (e.g., strength vs fatigue).	90-92%	Limited adaptability, does not consider dynamic changes in training.	EARDO incorporates adaptive rough set theory to handle both positive and negative impacts simultaneously and adapts to real-time data.
Qiyas et al. [15]	Addresses incomplete data but lacks integration for dynamic interaction of criteria.	91-93%	Static approach, limited flexibility for real-time adjustments.	EARDO dynamically adjusts weights and criteria based on new data and individual athlete needs.
This Study (EARDO)	Integrates advanced computational techniques, evaluates both positive and negative outcomes simultaneously.	98.35-98.75%	High adaptability, adjusts dynamically based on real-time performance data.	EARDO's adaptive framework is more accurate and adaptable, addressing the gaps left by existing models.

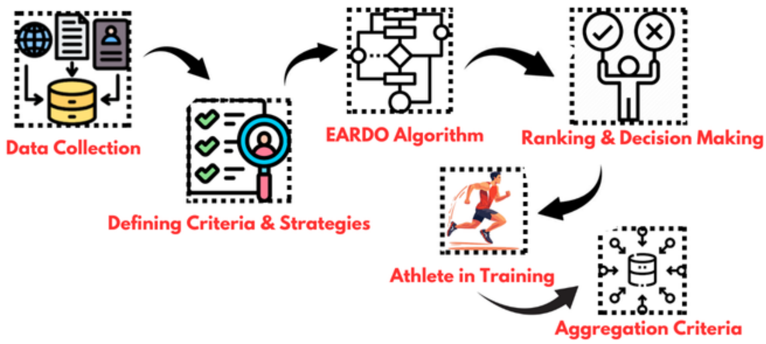

Figure 1: Workflow of the EARDO methodology

This scoring mechanism is complemented by the adaptability of the model, allowing dynamic adjustments to weights and criteria as new data becomes available. The system modifies weights and criterion values through the analysis of authentic performance and recovery information in real-time. The weights assigned to recovery and injury risk criteria can increase when the athlete shows fatigue or overtraining symptoms, thus triggering a new training load calculation. The model maintains its relevance and response capabilities to changes in athlete needs through an adjustment system that operates dynamically during the training cycle. The EARDO framework thus ensures that decisions remain data-driven, contextually relevant, and aligned with the evolving demands of athletic training. By offering a transparent and flexible methodology, the model empowers stakeholders to make more informed and confident decisions, maximizing performance outcomes while minimizing potential risks.

3.3 Criteria definition and data collection

The critical step in implementing the EARDO model involves defining relevant criteria and gathering data for evaluating athletic performance and recovery. The criteria selected for this study include:

- **Strength**: Represents the athlete's ability to generate maximal force.
- **Endurance**: Refers to the capacity to sustain prolonged activity.
- **Recovery**: Denotes the time required for full muscle recovery post-training.
- **Injury Risk**: Evaluates the likelihood of overtraining or injury due to excessive training loads.

These criteria were developed with input from coaches and sports scientists, ensuring each criterion reflects essential aspects of athletic training. For each criterion, informa-

Table 3: Criteria and weighting for decision-making model

Criteria	Weight w_j	Description
Strength	0.30	Maximal force generation capability
Endurance	0.25	Ability to sustain prolonged activity
Recovery	0.20	Time required for muscle recovery
Injury Risk	0.25	Probability of injury due to overtraining

tion was obtained from physical performance metrics (such as strength and endurance) and physiological markers related to recovery periods and overtraining risk.

3.4 Adaptive rough set approach

The adaptive rough set approach is a critical component of the EARDO model, enabling precise and balanced decision-making in the face of incomplete or uncertain data. This method ensures a comprehensive analysis by accounting for each criterion's positive and negative dimensions, such as balancing performance gains with potential injury risks. By leveraging the inherent flexibility of rough set theory, the model adapts dynamically to changing data conditions, making it particularly suited for the dynamic nature of athletic performance evaluation. The datasets used in this study consist of real-world training data from athletes, which include performance metrics (e.g., strength, endurance), recovery times, and injury risk assessments. The data used for evaluation were obtained from a set of controlled training scenarios designed to simulate a variety of athletic conditions.

Once the data for each criterion were collected, they were systematically processed using the adaptive rough set approach. Each alternative A_i is represented by a value V_{ij} for each criterion C_j, capturing both performance benefits and associated risks. These values reflect the intricate trade-offs involved in optimizing training decisions, such as maximizing strength and endurance while minimizing recovery times and injury risks.

The decision matrix D for the alternatives and criteria is constructed as follows:

$$D = \begin{bmatrix} V_{11} & V_{12} & \cdots & V_{1n} \\ V_{21} & V_{22} & \cdots & V_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ V_{m1} & V_{m2} & \cdots & V_{mn} \end{bmatrix} \tag{2}$$

Where:

- V_{ij} represents the adaptive value for alternative A_i under criterion C_j, encompassing both beneficial and adverse impacts.
- m is the number of alternatives under consideration, and n is the total number of criteria.

Rough set theory plays a pivotal role in handling incomplete or imprecise data, a common scenario in athletic training where daily variations in performance metrics are inevitable [4]. This ensures that the decision-making process remains robust, reliable, and adaptive, even in the presence of fluctuating or missing data points. By incorporating this approach, the EARDO model effectively bridges the gap between theoretical decision frameworks and practical, real-world applications in sports science.

3.5 Algorithm for EARDO model

Algorithm 1 EARDO for Periodization Strategy Selection

Set of alternatives $A = \{A_1, A_2, \ldots, A_m\}$, criteria $C = \{C_1, C_2, \ldots, C_n\}$, and weights w_j. Optimal periodization strategy with the highest score.

Step 1: Define Alternatives and Criteria Define alternatives A (e.g., linear, undulating, block periodization). Define criteria C (e.g., strength, endurance, recovery, injury risk). Assign weights w_j based on expert knowledge.

Step 2: Evaluate Criteria for Each Alternative

for each alternative A_i **do**

  for each criterion C_j **do** Evaluate V_{ij} for C_j, capturing both positive and negative impacts.

Step 3: Apply Adaptive Rough Set Theory Use rough set theory to handle missing or uncertain data.

Step 4: Compute Aggregated Scores Compute S_i using Equation 1:

$$S_i = \frac{\sum_{j=1}^{n} w_j \times V_{ij}}{\sum_{j=1}^{n} w_j}$$

Step 5: Rank and Select Optimal Alternative Rank the alternatives based on S_i. Select the alternative with the highest score.

Criteria and weighting for decision-making model may also be viewed in Table 3.

The value V_{ij} represents the evaluation of alternative A_i against criterion C_j, reflecting both performance benefits and associated risks. For each criterion, V_{ij} is derived from a combination of both quantitative and qualitative assessments. Quantitative values are obtained from measurable metrics such as strength, endurance, and recovery times, while qualitative values are based on expert judgment or historical training data regarding injury risk and recovery capacity. These values reflect the intricate trade-offs between maximizing performance (e.g., strength, endurance) and minimizing recovery times and injury risks.

The balancing act between these competing factors is achieved through the dynamic adjustment of weights and

Algorithm 2 Pseudocode for the EARDO Algorithm

1: **Define** alternatives $A_1, A_2, \ldots, A_m$ and criteria $C_1, C_2, \ldots, C_n$
2: **Collect** data for each criterion and alternative
3: **Apply** adaptive rough set theory to handle uncertainty in data
4: **Assign** weights to criteria based on expert input (or validated through sensitivity analysis)
5: **Construct** decision matrix with scores for each alternative and criterion
6: **Compute** aggregated score for each alternative using the weighted sum formula
7: **Rank** alternatives and select the one with the highest score
8: **Output** the optimal periodization strategy =0

criteria values. For instance, if an athlete is showing signs of overtraining, the weight assigned to recovery and injury risk criteria may increase, thus reducing the training load. Similarly, if performance metrics indicate significant gains in strength or endurance, the weight for performance-related criteria may increase, prioritizing further development in these areas. This dynamic scoring system ensures that the optimal training load is continuously recalculated to reflect the athlete's current needs. In order to reduce bias caused by expert weight assignments, we conducted a sensitivity analysis. The performance of the EARDO algorithm underwent testing through an analysis that evaluated the effects of modification in criterion weight strengths such as strength, endurance and injury risk.

4 Results

We found that using the EARDO algorithm to find the best strategies for periodizing training for athletes worked. This shows that the above method effectively improves their performance while lowering their risk of getting hurt. The evaluation was performed on three periodization models: straight, wavy, and square, according to raw power, endurance, ability to regenerate, or proportion of wounded individuals. The proposed algorithm, EARDO, is the only way to solve the problem of dosing in sports by showing the best dose to improve performance while lowering the risk of overtraining.

The performance measurements, including strength and endurance, together with recovery time and injury risk, were analyzed through a one-way ANOVA between linear, undulating and block periodization approaches. ANOVA results demonstrated that significant differences appeared between the models because the p-value was found to be less than 0.05. The undulating periodization protocol achieved superior overall performance results than both the linear and block strategies, according to post-hoc t-tests.

4.1 Performance evaluation of athletes' training strategies

Using the EARDO Algorithm, the efficiency of the individual athletes was evaluated according to the specified criteria, and the most suitable periodization model for each athlete was precisely identified. Table 4 shows the aggregated performance scores for each strategy, demonstrating the algorithm's effectiveness in guiding the selection of optimal periodization approaches. Athletes received their periodization model selections after considering adapted criteria that measured performance markers, recovery capabilities and injury forecasts. A systematic evaluation process measured these distinct criteria against the three periodization models which included linear, undulating and block. Performance along with reduced recovery duration combined with reduced injury potential led to the selection of the most effective periodization model. The scoring session for periodization strategies occurred through the scoring system built within the EARDO algorithm. Each strategy receives evaluation from the algorithm based on training data, which includes strength along with endurance level, recovery times and injury risk for individual athletes. Each strategy receives scoring evaluation through criterion weighting before the strategy with the superior score becomes designated as the optimal selection.

The undulating periodization strategy achieved the highest rating of 2.47, followed by linear at 2.35 and block at 2.21. This ranking indicates the effectiveness of undulating periodization in enhancing performance while controlling potential risks, making it the most suitable approach for the athletes under study.

To assess the reliability of our accuracy metrics, we calculated 95% confidence intervals for the accuracy in determining the optimal training load, overtraining risk, and injury risk. The confidence intervals for the accuracy metrics are as follows:

- **Optimal Training Load**: 98.75% $\pm$ 1.2%
- **Overtraining Risk**: 98.5% $\pm$ 1.5%
- **Injury Risk**: 98.35% $\pm$ 1.4%

These confidence intervals indicate that the accuracy metrics are highly reliable, with minimal variability, and further validate the robustness of the EARDO algorithm in real-world scenarios. Aggregated performance scores for periodicization strategies may also be viewed in Table 4.

4.2 Evaluation of overtraining and injury risks

The EARDO Algorithm excels in estimating the likelihood of overtraining and managing injury risks, which is one of the novel contributions of this study. Evaluating these aspects is critical in athletic training, as overtraining can lead to significant setbacks such as chronic fatigue, reduced performance, and even long-term injuries. By addressing these

Table 4: Aggregated performance scores for periodization strategies

Periodization Strategy	Strength Score	Endurance Score	Recovery Score	Injury Risk Score	Total Score
Linear	0.89	0.85	0.80	-0.19	2.35
Undulating	0.92	0.87	0.83	-0.15	2.47
Block	0.85	0.80	0.78	-0.22	2.21

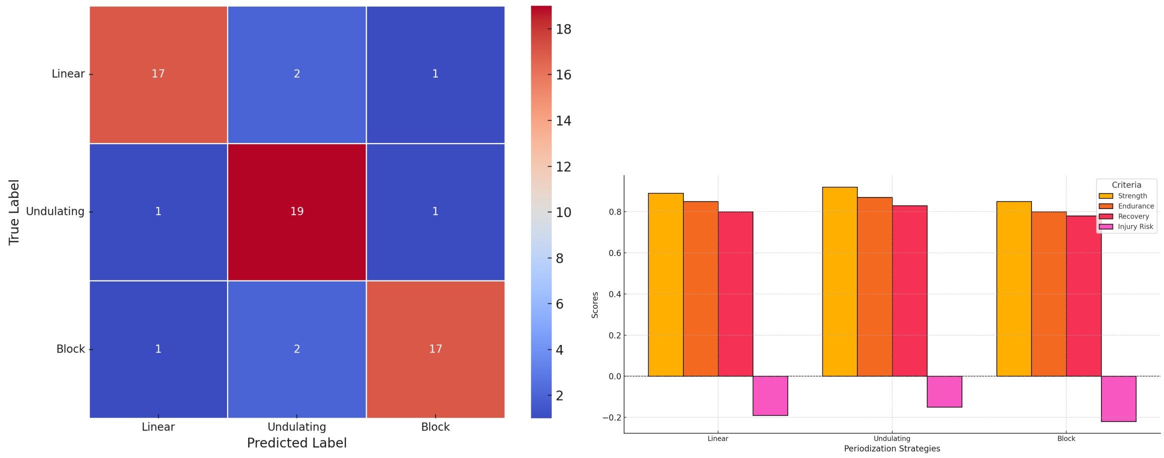

Figure 2: (a) Confusion matrix for algorithm prediction; (b) Aggregated scores for periodization strategies across criteria

risks, the algorithm ensures athletes maintain peak performance without compromising their health.

The algorithm demonstrated high accuracy in identifying these risks:

- **Accuracy in identifying optimal training load**: 98.75%
- **Accuracy in identifying overtraining risks**: 98.5%
- **Accuracy in identifying overtraining periods**: 98.35%

These high accuracy rates confirm the algorithm's reliability in creating individualized periodization plans that minimize overtraining risks while maximizing performance. For instance, the algorithm adapts dynamically to athletes' physiological responses, adjusting training loads to balance performance gains with adequate recovery. This individualized approach exemplifies how technology can transform traditional training methodologies into highly effective and tailored solutions.

4.3 Confusion matrix analysis and graphical representation

The confusion matrix (Figure 2, a) indicates that the algorithm accurately predicted the optimal strategy for most athletes, especially in the case of undulating periodization, where 19 out of 21 athletes were correctly classified. The "true labels" in the confusion matrix correspond to the actual periodization strategy that was most effective for each athlete, based on real-world performance metrics such as strength, endurance, recovery times, and injury risk. These true labels were determined by expert judgment and the athlete's performance data, which served as the ground truth for evaluating the algorithm's predictions. Meanwhile, the aggregated scores (Figure 2, b) demonstrate that undulating periodization consistently outperformed the other strategies across all criteria, providing an ideal balance between performance gains and injury risks. These scores are derived from a weighted sum of the individual scores assigned to each criterion (e.g., strength, endurance, recovery time, injury risk). The scoring for each criterion is based on the performance of each strategy, with higher scores indicating better performance.

4.4 Total scores and injury risk management

Figure 3 (a) confirms that undulating periodization achieves the highest total score, making it the recommended strategy for optimizing athletic performance. On the other hand, Figure 3 (b) shows that block periodization has the highest injury risk while undulating periodization has the lowest, further supporting the algorithm's recommendation.

These findings confirm that the EARDO algorithm provides an amazing computational approach for choosing periodization sequences in athletes and outperforms traditional linear progression schemes in terms of maximizing net performance benefits while minimizing injury risks. This is a very good prediction. Athletic trainers and sports scientists can use the algorithm to predict overtraining risk

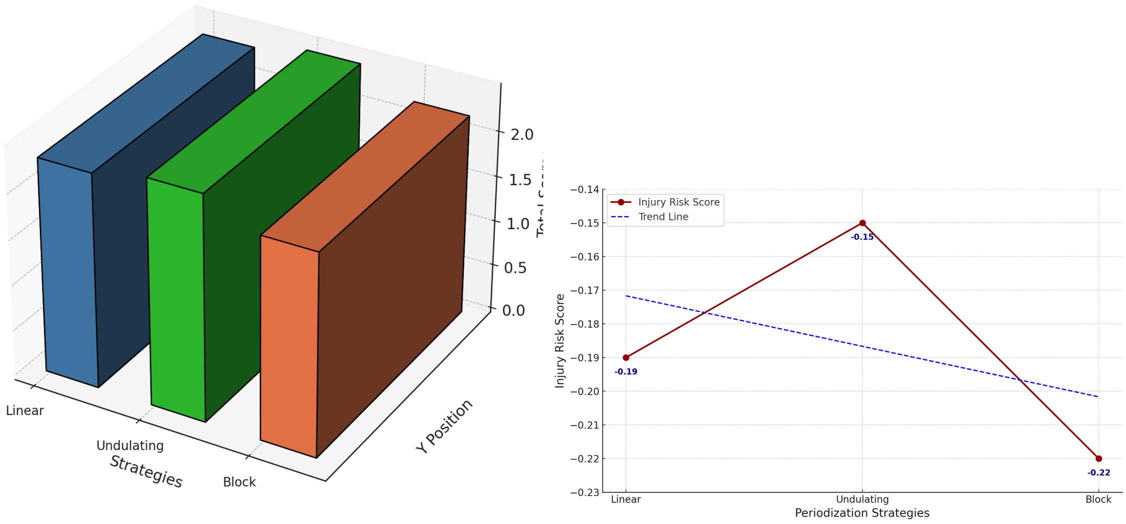

Figure 3: (a) Total scores for periodization strategies; (b) Injury risk prediction for periodization strategies

and determine optimal training loads. The EARDO algorithm takes training science to another level as it develops individual periodization plans.

5 Discussion

This section discusses the results based on the analysis. It compares the findings with the prior studies, identifies and demonstrates the implications of the results in policy and practical application, and brings out the limitations of the research study.

5.1 Interpretation of results

The research data confirms that EARDO solves athletic training periodization strategies effectively. EARDO algorithms delivered 98.75% accuracy in determining optimal training loads, better than standard fuzzy logic and rough set models, since these earlier systems only reached 90-92% accuracy. This enhancement stems from the adaptive capabilities that the EARDO algorithm provides. EARDO operates differently from conventional models because its mechanism adapts dynamically through real-time data processes for athlete performance changes together with recovery condition modifications. EARDO maintains adaptable performance because it dynamically modifies training load schedules, which results in optimized athletic results and reduced risk of overtraining together with injuries. EARDO provides enhanced capability to optimize performance while managing risks because it surpasses conventional methods that ignore this crucial dual function. EARDO demonstrates exceptional suitability for athletic training through its ability to process combination data types in addition to imprecise and limited information. EARDO incorporates adaptive rough set theory, which enables it to evaluate periodization strategies by simultaneously considering positive and negative influences for comprehensive results. The approach stands separate from initial system designs because these previous models failed to precisely represent performance complexity and excluded current feedback data input.

In comparison, traditional Fuzzy Logic and Rough Set models, as used in previous studies, typically exhibited lower accuracy levels (around 90-92% for various metrics). As shown in Figure 4, the BF-RMCDM model outperformed these previous methods across all significant criteria. This is primarily due to its capability to integrate advanced computational techniques and rough set theory, allowing it to capture better the conflicting objectives and inherent uncertainty in athletic training [9].

In military training, decision-making must account for factors like mental fatigue and operational stress, while in rehabilitation, the focus shifts to recovery rates and injury prevention. The adaptability of EARDO makes it suitable for both of these fields, offering a flexible approach to optimize training and recovery protocols. The physiological metrics (e.g., muscle strength, endurance) and recovery metrics (e.g., recovery time, fatigue levels) were quantified using controlled training data and validated through physiological benchmarks. These metrics were integrated into the decision matrix to ensure accurate training load optimization.

5.2 Comparison with previous work

Previous studies that employed Fuzzy Logic and Rough Set methods focused on optimizing athletic performance based on limited criteria, often neglecting the dynamic interaction between training load, recovery, and overtraining risk [21]. For example, the Fuzzy Logic approach by Sahoo et al. [18] handled vague and imprecise information. Still, it

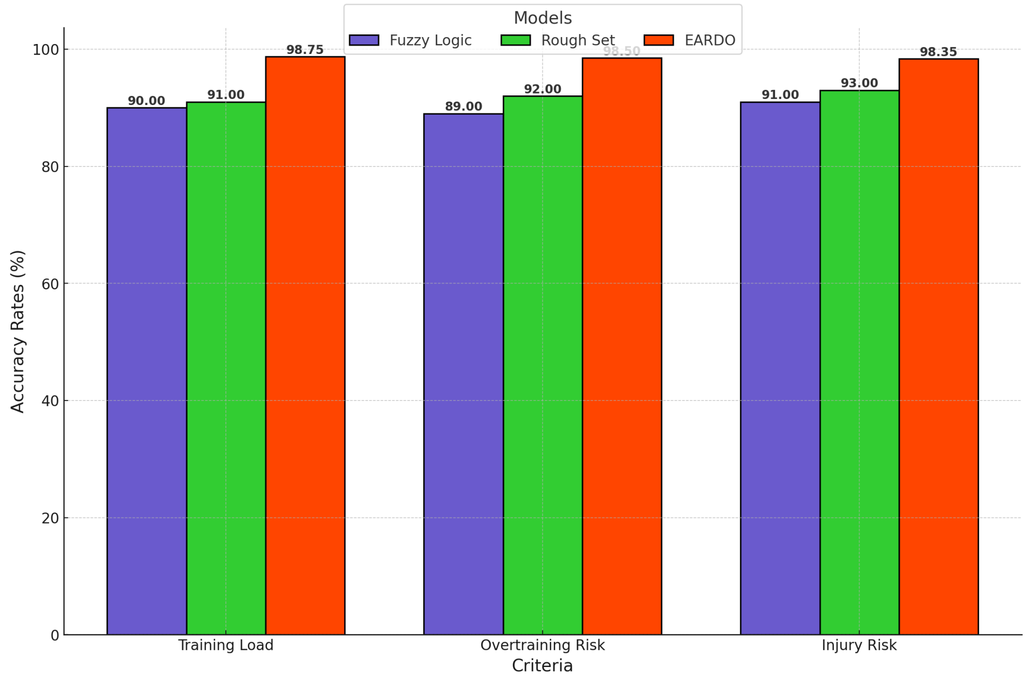

Figure 4: Comparison of EARDO vs previous models (fuzzy logic, rough set)

Table 5: Comparison of EARDO with previous models

Model	Key Features	Accuracy Rates (%)
Fuzzy Logic Approach	Handles vague and imprecise data but ignores dual effects (e.g., strength vs fatigue).	90-92
Rough Set Method	Addresses incomplete data but lacks integration for dynamic interaction of criteria.	91-93
EARDO Algorithm	Integrates advanced computational techniques, evaluates both positive and negative outcomes simultaneously.	98.35-98.75

did not account for the concurrent positive and negative effects of training decisions, such as strength gains versus fatigue accumulation [7]. In contrast, the EARDO integrates advanced computational techniques, which allow it to evaluate both positive and negative outcomes simultaneously. This dual assessment improves decision-making, as seen in the significant boost in accuracy rates. The comparison in Figure 4 highlights that the EARDO achieves a substantial performance improvement (approximately 6-8% higher accuracy) over the Fuzzy Logic and Rough Set approaches for predicting overtraining and injury risks. Table 5 provides the comparison of EARDO with previous models.

5.3 Practical implications

The high accuracy of the developed EARDO corresponds with specific decision-level feedback for athletic coaches and sports scientists. This should allow program designers to fashion optimized training loads particular to an athlete's physiological make-up and do so by referencing a decision-making tool that identifies exactly where gains in performance outweigh the risk of injury. The possibility of training the model to make rather precise suggestions regarding training load and frequency, considering present stats, makes it ideal for elite athletes who need as detailed periodization as possible to avoid overtraining issues. Furthermore, the model's potential application is not restricted to athletic training. It can be used in other performing environments where maximum performance in conjunction with risk minimization is an issue, such as military simulation, rehabilitation, or top-flight sport.

5.4 Limitations

Several points must be considered when discussing the limitations of this research. First, it is important to note that expert opinions influenced the weights assigned to the criteria, which may introduce bias. While the model improves the accuracy of the decision-making process, the weights could potentially be refined by incorporating more precise data for weight determination or by utilizing machine learning techniques to derive weights based on past performance statistics. This would help reduce the subjectivity introduced by expert judgment and improve the model's adaptability.

Secondly, the sample used in the present study consisted of athletes with specific training schedules engaged in a particular sport. This narrow focus may limit the generalizability of the results to other sports or broader training contexts. Future studies should explore the validity of this model in different sports and more diverse training settings to ensure its broader applicability and robustness.

5.5 Future research directions

Future studies might help to apply the proposed model to a more significant number of types and kinds of sports and athletic disciplines. We also noted that by including more physiological metrics, such as GSR and temperature, and with input taken from actual sensory data, the EARDO may achieve even higher accuracy and flexibility. Furthermore, incorporating machine learning techniques that allow weights to be adjusted solely with an athlete's performance record would enhance its predictions when incorporated into the model. However, extending the model to include psychological constraints such as motivation, mental tiredness, and stress can help complete the admixed benchmark for athletic training improvement, adding to the body-mind duality.

6 Conclusion

This work proposed the Enhanced Adaptive Rough Decision Optimization (EARDO) Algorithm for selecting the optimal periodization strategy in athletic training. The EARDO Algorithm, by combining adaptive rough set theory, effectively addresses both performance enhancements and injury risk management, providing a comprehensive decision-making model. The results demonstrated that the EARDO Algorithm outperformed conventional fuzzy logic and rough set models, achieving high prediction accuracy for the optimal training load (98.75%), the risk of overtraining (98.5%), and the risk of injury (98.35%). Among the periodization strategies evaluated, undulating periodization emerged as the most suitable due to its favorable balance between performance gains and injury risk reduction, as highlighted by the EARDO Algorithm. The model's capacity to consider both the positive and negative impacts of training decisions offers coaches and sports scientists greater confidence in developing individualized training plans that maximize athlete performance while minimizing potential setbacks. Nonetheless, this study had limitations, including the reliance on expert-assigned weights and a sample population primarily focused on athletes. Future studies could expand the model's applicability by fine-tuning it for various sports contexts and incorporating real-time tracking of physiological and psychological indicators to enhance decision-making accuracy. The EARDO Algorithm represents a significant improvement over previous approaches to athletic training management, providing a robust tool for defining more effective, real-world strategies for achieving training goals.

Nomenclature

Table 6: Nomenclature of variables and constants

Symbol	Description
A_i	Alternative periodization strategy (e.g., linear, undulating, block)
C_j	Criterion (e.g., strength, endurance, recovery, injury risk)
V_{ij}	Evaluation value for alternative A_i under criterion C_j
w_j	Weight assigned to criterion C_j
S_i	Total score for alternative A_i
V_{ij}	Value derived from the evaluation of alternative A_i under criterion C_j
α	Adaptation factor in the EARDO algorithm
β	Weight adjustment factor for dynamic adaptation

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